Chasing Private Information*

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Abstract

Do market-based signals reveal the trading of privately informed investors? We examine this question using a novel sample of over 5,000 equity and option trades documented in the SEC's insider trading investigations. We find that: (1) Trades based on information about fundamentals do impact information signals. (2) The relation between private and public signals is complex and, for commonly used liquidity metrics, contrary to standard theories. (3) Trade volume is more informative in option markets than in stock markets, with the combination of both being most informative. Evidence from the SEC's Whistleblower Reward Program addresses potential selection concerns.

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1 Introduction

Information asymmetry is ubiquitous in financial markets. The presence of informed market participants is widely believed to affect the behavior of asset prices, as well as corporate decisions. Various information-based trading theories argue that uninformed investors update their beliefs about informed trading based on publicly observed signals, such as volume or market prices.[1] While these information signals may provide useful guidance, it is difficult to assess empirically how much information they truly reveal, because the information sets of investors are almost never observable. Hence, most empirical efforts to empirically test the predictions of these theories suffer from the joint hypothesis problem that makes it difficult to attribute any dynamics of public signals to the arrival of nonpublic information. For example, changing levels of prices may reflect time-varying risk premia. Similarly, changing volume levels may be due to a systematic liquidity component or uninformed demand pressure.[2]

We address this identification challenge by focusing solely on trades that are unequivocally based on nonpublic information about firms' fundamentals. Our inference utilizes a hand-collected sample of insider trading cases prosecuted by the U.S. Securities Exchange Commission (SEC) that document in detail how certain individuals trade on nonpublic and material information. These cases involve a large number of trades in several hundred firms over the period 1995-2015 and, hence, they are representative of a fairly large universe of assets and market conditions. A key advantage of using insider trading is that we can observe the dynamics of market signals when private information arrives in the market. Our ability to observe the arrival of private information directly is in stark contrast to prior literature, which typically infers the presence of informed trading indirectly, either by observing the trading behavior of financial professionals (e.g., institutional investors or large

[1]Theories of learning from prices originate in the seminal papers of Grossman (1976) and Grossman and Stigliz (1980) and also include the works of Hellwig (1980), Admati (1985), Glosten and Milgrom (1985), Kyle (1985), and Holden and Subrahmanyam (1992). Studies with trading volume as a signal include those of Admati and Pfleiderer (1988), Kim and Verrecchia (1991), Easley and O'Hara (1992), Campbell et al. (1993), Wang (1994), He and Wang (1995), and Schneider (2009).

[2]Moreover, most theory-motivated information signals, such as the bid–ask spread and the price impact of trades (Glosten and Milgrom, 1985; Kyle, 1985), rely on the notion that the presence of informed traders is common knowledge to other market participants. More realistically, market participants need to infer not only whether bad or good news arrives but also the arrival of news in the first place (e.g., Easley and O'Hara, 1992; Banerjee and Green, 2015).

activist shareholders), trading ahead of important information events (e.g., earnings announcements or mergers), or trading in assets with different characteristics (e.g., volatility, size, growth).

Guided by prior theoretical and empirical research, we consider three groups of information signals: those based on stock data, those based on option data, and those combining stock and option data. Each signal is a function of prices, volume, or a combination of the two. We hypothesize that, if the presence of an informed trader has a traceable impact on public signals, abnormal behavior should be displayed on days with informed trading relative to a sample of random dates. We document three main results: (1) Trades based on private signals about the value of the underlying asset have an impact on the behavior of public signals. (2) The relation between private and public signals is complex and, in several cases, including commonly used liquidity metrics, contrary to standard theories. (3) Trade volume is more informative in option markets than in stock markets. The combination of the two, however, is most informative.

Our empirical tests use a comprehensive sample of 453 insider trading cases filed by the SEC over the period 2001–2015. Each case includes a detailed description of situations in which individuals trade while exploiting material and nonpublic information. For example, a hedge fund trader personally linked to a given firm's chief financial officer could privately learn about exceptionally high quarterly earnings and acquire shares of the company in advance of the company's report. We collect all available details about the motivating information, the identities of the individual traders, the assets and exact trading dates, and the trade execution (e.g., prices and quantities). We additionally trace the dates when the motivating information is released to the public. Notably, there is no uncertainty as to whether the underlying information is private. Our final sample contains 5,058 trades in 615 firms that represent the vast majority of industry sectors.

At the outset, we evaluate the economic characteristics of our sample. First, we assess the strength of the information on which individuals in our sample trade by computing hypothetical stock returns (excluding dividends) that an investor would realize if the investor initiated his or her trade at the opening price of the day the insider first trades and closed her trade at the opening price of the day following the public information disclosure. We show that, on average, such returns exceed 40% for private signals with a positive sign and 20% for those with a negative sign. Both results are economically large, especially since they accrue over a relatively short period of seven days, on average. These figures could, in fact, underestimate the pre-fees profits of the informed traders, since 30% of the trades in our sample are executed using options, not stocks.

Second, we document the stylized characteristics of the traders. Our sample contains both individuals with a small amount of available capital, wealthy individual investors, and institutional investors such as hedge funds (e.g., Galleon Group, SAC Capital). It is worth noting that a substantial fraction of individuals work in the finance industry or have top executive jobs; hence, they exemplify how skilled investors trade. Finally, we document informed volume. We show that, on days when insiders trade, their trades constitute more than 10% of the total volume for stocks and more than 30% for options. Overall, we argue that our sample reflects the trades of an economically relevant group.

In our main empirical test, we evaluate whether various information signals (IS) display abnormal behavior on days when insiders are trading. The underlying identification idea is that, as is common in the literature (e.g., Easley and O'Hara, 1992), privately informed traders are not present every single trading day for any given asset. We can then succinctly express the value of a given information signal i as

$$E\left[IS_{i,t} \middle| \text{ info trade on day } t\right] = E\left[IS_{i,t} \middle| \text{ no info trade on day } t\right] + \Delta_i, \tag{1}$$

where Δ_i represents the impact of informed trading on information signal i. For concreteness, consider the bid–ask spread as an IS example. The mean conditional on no informed trading could reflect factors such as inventory or order processing costs, while $\Delta_{bid-ask}$ captures the adverse selection component on days with informed traders (Glosten and Milgrom, 1985). The coefficient Δ should be statistically significant if a particular signal reveals the presence of informed trading. Standard economic theories discussed in Section 2, in turn, inform us about the expected sign of Δ_i for a each signal i. To implement the test, we consider a simple difference-in-differences framework in which the values of signals on days with informed traders, adjusted by the corresponding values from control assets, are compared to the values recorded on days preceding the informed trades (21 to 35 trading days prior).

Our first key result is that trades based on private information about firms' fundamentals do have an impact on the behavior of the information signals considered. In other words, information signals do display abnormal behavior when informed participants trade, in both stock and options markets. Of the nine stock-based signals we consider, six are statistically significant in a model that includes both firm and time-fixed effects and benchmarks the affected companies against a portfolio of firms in the same two-digit Standard Industrial Classification (SIC) industry with a similar market capitalization. However, *only one* of them–price range–changes in the direction predicted by theory. Notably, the quoted bid--ask spread, absolute order imbalance, and illiquidity are negatively related to instances of informed trading. Option-based signals, we find, also display abnormal behavior. Seven out of eight signals are statistically significant using the same specification. However, a greater proportion of them go in the direction predicted by theory, including implied volatility (IV) and abnormal volume. Again, both the bid–ask spread and illiquidity are negatively related to insider trading. Finally, we consider mixed-market signals and find that those that relate option volumes to the corresponding equity volumes, either for all types of contracts, or calls and puts taken separately, are reliable indicators of the presence of informed trading. Signals that capture cross-liquidity effects between stock and option markets, instead, display abnormally low values. Our results then suggest that the relation between private information and the behavior of liquidity and volatility measures is complex and not identical across asset markets. Moreover, our results suggest a strong information content of option markets. This finding is particularly interesting, since prior research has mostly focused on stock-based signals to identify the presence of informed trading.

Since our sample consists solely of SEC-investigated insider trading violations, one could be concerned about a potential sample selection bias. In particular, an important selection concern would be that insider traders are exposed *only* when information signals display abnormal values.[3] This could be the case if the SEC's detection technology followed a similar set of results as those we document. In this case, one would overestimate the information signals' capacity to detect

[3] An alternative hypothesis is that the SEC investigation causes certain signals to be informative. However, this is, of course, not possible, since the investigation always happens after the fact, on average, two years after (Augustin et al., 2015).

information. We do not ex ante believe such a possibility is very likely, since many cases are often investigated based on external referrals and not based on the SEC's screening of, say, liquidity metrics. Nevertheless, we provide a battery of tests to address this possibility more formally. First, we take advantage of the 2010 adoption of the SEC Whistleblower Reward Program, which offers monetary rewards to individuals who provide useful tips to uncover illegal insider trading. The main identifying assumption of this test, as stipulated by the regulation, is that such cases are investigated by the SEC for reasons other than the behavior of publicly available data. We show that the dynamics of public signals do not depend significantly on the origin of the investigation. Second, we follow Meulbroek (1992), who argues that the investigation trigger in cases that involve a large number of firms (complex cases hereafter) is, for each firm involved, less likely to stem from trading patterns. We show that case complexity does not alter the results. We further show that our findings are not significantly affected by the profitability of each individual trade. Finally, we show that other plausibly relevant event dates, such as the arrival of private information (tips) or public events, do not exhibit similar dynamics in public signals. Overall, our results strongly suggest that the thrust of our findings is unlikely to reflect selection biases.

Next, we conduct a number of tests to provide additional insights into our results. First, we find that large trades strengthen the results of baseline tests. Second, we show that the ability of public signals to reveal informed trading decreases for trades executed by traders with relatively high expertise. This finding suggests that such traders are more able to hide their intentions from the public. Third, we find that the stock-based and option-based signals reveal more information ahead of unscheduled events, such as mergers and acquisitions (M&As), compared to scheduled events, such as earnings announcements. We conjecture that scheduled events could foster uninformed directional bets that introduce additional noise. In turn, mixed-market signals are almost equally strong ahead of both types of events. Moreover, the signals considered reveal more information in anticipation of positive news than negative news, which indicates that informed traders could be subject to short-selling or option availability constraints. Fourth, we study the cross-sectional determinants of information signals utilizing volumes from option and stocks markets. Our results are strongest for signals that consider relatively short-term (between 10 and 60 days) and levered (out-of-the money) contracts, which is consistent with the view that informed trading is primarily executed in "inexpensive" contracts that could relieve capital constraints (Black, 1975).

In a final set of tests, we further explore the negative relation between illiquidity and informed trading. Such connection could be rationalized by informed traders who strategically choose the execution time of their trades, trading relatively more on days when liquidity is high. To shed light on this hypothesis, we exploit one distinctive feature of our data: the ability to observe when private information is received by a trader. When all assets are considered, we show that the same negative relation exist for trades in which the timing ability is low because the information is of short duration (the information is received within three trading days of the public disclosure of information). Interestingly, however, we do find that the negative relation is almost entirely driven by small stocks, a finding that is consistent with the view that such companies are less liquid and thus more prone to strategic timing. In a similar fashion, we show that the negative relation is stronger for companies that do not have listed option contracts. The finding that quoted spreads also display abnormally low values for small stocks also suggests that informed traders are more likely to trade using limit orders when receiving tips on small firms.

Literature Review. Our paper spans several strands of literature. First, we contribute to the literature on the informational content of stock and option prices. The theoretical literature has identified links between private information and the liquidity of stocks (e.g., Glosten and Milgrom, 1985; Kyle, 1985; Easley and Hara, 1987), the liquidity of options (e.g., Biais and Hillion, 1994; Easley et al., 1998), the volatility of stock prices (e.g., Wang, 1993), and the volatility of options (e.g., Back, 1993). Our information signal candidates are motivated by this literature and the corresponding empirical work.[4] However, empirically, we know little about how much information is revealed in such signals, which is the main focus of our paper. A notable exception is recent work by Collin-Dufresne and Fos (2015), who identify a negative relation between the trading behavior of activist investors and liquidity measures for stocks, which they attribute to the strategic behavior of such investors. Our results from stock data are consistent with the authors' results; at the same time, the conclusions we draw from the option data are the opposite. One argument to reconcile

[4] Vayanos and Wang (2013) and Goyenko et al. (2009), among others, provide thorough reviews of the theoretical and empirical literature.

the apparent differences is that, unlike our traders, activist investors do not trade much in options, possibly because their trades are not motivated by corporate events but, rather, by their perceived ability to gain control and change corporate strategies in the long run.

Second, we contribute to the literature on private information in trading. Prior research has taken different approaches to identify informed trading. A large body of papers analyze and apply the probability of informed trading (PIN) model (Easley et al. 1996a; 1996b).[5] Boulatov et al. (2013) and Hendershott et al. (2015) identify information based on institutional order flow. Kacperczyk, van Nieuwerburgh, and Veldkamp (2016) use a model with endogenous information acquisition to infer private information in a sample of mutual funds. A different approach has been to look at trading behavior of finance professionals, such as asset managers (e.g., Kacperczyk and Seru, 2007; Cohen, Frazzini, and Malloy, 2008; and Kacperczyk, van Nieuwerburgh, and Veldkamp, 2014), retail investors (Kelley and Tetlock, 2013), corporate insiders (Cohen, Malloy, and Pomorski, 2012), and activist investors (Collin-Dufresne and Fos, 2015; Collin-Dufresne et al., 2016). Yet another approach has been to look at trading patterns ahead of important information events. Ali and Hirshleifer (2015) identify informed insider trading based on the profitability of trades prior to earnings announcements. Augustin et al. (2015) study option trading prior to M&As activity and tests whether abnormal trade volume is linked to private information by predicting subsequent M&A events.

While all the above approaches have merit, ultimately, they are unable to definitely answer whether certain individuals indeed acted upon private information when trading. To the best of our knowledge, the only other studies that have examined flows of private information in financial markets, to analyze different economic issues are those of Koudijs (2015, 2016) for the 18th-century London and Amsterdam markets. While in Koudijs' framework one can plausibly identify the arrival time of private news, one cannot observe the precise nature of information or how individual traders

[5]The structure of the PIN model has been enriched and extended by, among others, Easley et al. (2008) and Duarte and Young (2009). Odders-White and Ready (2008) consider a Kyle-type model and allow for the amount of information to be separated from the probability of arrival. Most of these papers assume that informed traders do not respond to price changes. In contrast, Back et al. (2016) analyze a model with a PIN-like information structure but where a single informed trader acts strategically, as for Back (1992), and conclude that private information cannot be identified using order flow alone. Further, a number of papers analyze the performance of the PIN model (e.g., Brennan et al., 2015; Duarte et al., 2016).

use it in real time. These elements are crucial to our work.

Finally, we also contribute to the literature on the market impact of insider trading, especially that which explicitly considers the SEC's litigation files. Meulbroek (1992) examines the impact of illegal trading on stock returns and market efficiency using a sample of legal cases from the 1980s. The author shows that insider trades affect returns, as predicted by standard theory. Cornell and Sirri (1992) present a single-company case study of the impact of insider trading on stock liquidity. More recently, Del Guercio et al. (2015) study the effect of a time-varying legal enforcement environment on price discovery.[6] Kacperczyk and Pagnotta (2016) explicitly study the design of trading strategies by informed insiders.

The remainder of the paper proceeds as follows. Section 2 discusses the theories motivating the information signals candidates and their empirical counterparts. Section 3 describes the sample of insider trading cases. Section 4 presents our main empirical results. Section 5 discusses various identification issues. Section 6 discusses various cross-sectional tests, while Section 7 provides additional evidence on the behavior of liquidity metrics. Section 8 concludes the paper.

2 Signals of Private-Information-Based Trading

In this section, we summarize various signals that we use as candidates to identify the presence of privately informed investors. Our choice of the signals is dictated by related theoretical models, as well as their popularity in empirical studies. We discuss the connections between theories of informed trading, the behavior of the information signals, and the empirical implementation. For clarity of exposition, we distinguish between signals that are based on stock data, option data, and a mixture of the two. Further, within each asset class, we group signals according to whether they are based on price, volume, or a combination of these. When considering a particular signal, the subindex s (o) denotes stock (option) data. Table I summarizes all the signals using this classification. Further details about the data are discussed in Section 2.4.

[6] Bhattacharya (2014) provides an excellent review of the literature on insider trading. From a different perspective, Ahern (2015) provides a description of insider trading networks.

Table I
The Matrix of Signals

Signal/Market	Stocks	Stock options	Mixed-market
Price-based	Quoted Spread, Price Impact Price Range, Realized Variance Price Informativeness	Quoted Spread Implied Volatility (IV) IV Skewness	Quoted Spread Ratio
Volume-based	Abnormal Volume Absolute Order Imbalance	Abnormal Volume Volume Ratio (out of the money, all)	Volume Ratios (O/S, C/S, P/S)
Price– and volume-based	Illiquidity Lambda	Illiquidity	Illiquidity Ratios (O/S, S/O)

2.1 Private Information in Stock Markets

In competitive models of privately informed traders—for example, see Grossman and Stigliz (1980), Hellwig (1980), Admati (1985), and Easley and O'Hara (2004) for stock markets and Brennan and Cao (1996) for option markets—price and volume are jointly determined as a function of the fraction of informed traders and their information precision. Because each investor is an infinitesimal unit, the leakage of material nonpublic information to a given individual has no directly observable consequences. Models in this tradition have implications for price informativeness rather than liquidity measures. The theories that we highlight in the remainder of this section typically consider some form of imperfect competition in the use of information instead.

Price-Based Signals.

In the sequential trading model of Glosten and Milgrom (1985), the presence of informed traders causes the bid–ask spread to increase. Easley and Hara (1987) extend this model and show that the prices that market makers post depend on the size of the order. In this spirit, we use the average quoted bid–ask spread for a given stock. Further, we follow Glosten and Harris (1988) and Huang and Stoll (1996) and consider related measures of trading costs: the effective spread, the realized spread, and the order price impact. We only present detailed results for the last one.

Traditionally, the presence of informed traders is associated with more stable prices. This is because informed investors take profitable positions whenever the price deviates from fundamentals.

The more informed traders, the larger their impact on the price and the less it can deviate from fundamentals (e.g. Campbell and Kyle, 1993). However, others argue that the relation is not straightforward (e.g., DeLong et al., 1990). Wang (1993) explicitly analyzes a dynamic asset pricing model with asymmetric information and risk-averse agents and finds that the effect on returns and volatility is ambiguous. On the one hand, the presence of traders with superior information induces uninformed traders to demand a larger premium for adverse selection risk. However, the trading by the informed investors also makes prices more informative, thereby reducing uncertainty. To shed light on the connection between privately informed trades and volatility we consider three specific signals: the daily price range, the intraday realized variance, and price informativeness.

Formally, we define all the stock price-based signals as follows.

Quoted Spread. Let t and k index trading dates and generic intra-day observations, respectively. The quoted bid–ask spread for a given stock is given by

$$\text{Quoted Spread}_{s,t} = \sum_{k=1:K} \omega_k \left(\frac{a_k - b_k}{m_k} \right),$$

where b and a denote the best bid and offer (BBO) quotes, $m \equiv \frac{1}{2}(a+b)$ denotes the midpoint, and ω_k represents a weight that is proportional to the amount of time that observation k is in-force.

Price Impact. The five-minute price impact is given by

$$\text{Price Impact}_{s,t} = \sum_{k=1:K} 2\omega_k d_k \left[\ln(m_{k+5}) - \ln(m_k) \right],$$

where m_{k+5} is the midpoint of the consolidated BBO quotes prevailing five minutes after the k-th trade, d_k is the buy–sell trade direction indicator (+1 for buys, –1 for sells), and ω_k represents a dollar weight for the k-th trade. This signal represents the permanent component of the effective spread and, intuitively, it measures gross losses of liquidity demanders due to adverse selection costs.[7]

Price Range. We define the daily price range as

[7] Two related signals are the effective spread and the realized spread. We tested these measures and the results are very similar to those of the price impact and are thus omitted.

$$\text{Price Range}_{s,t} = \frac{a_{\max,t} - b_{\min,t}}{m_t},$$

where $a_{\mathrm{max,t}}$ and $b_{\mathrm{min,t}}$ denote the maximum offer price and the minimum bid price, respectively, on day t; m_t is the arithmetic average of the two quantities. Price Range can be seen as a measure of both price dispersion and liquidity (e.g., Corwin and Schultz, 2012).

Realized Variance. We also consider the standard realized variance (RV) specification based on five-minute intervals. We express it as a percentage per day.

Price Informativeness. Roll (1988) argues that firm-specific variation is largely unassociated with public announcements and therefore largely due to trading by investors with private information. Extending the author's argument, we hypothesize that greater firm-specific variation indicates more intensive informed trading and, consequently, more informative pricing. Our implementation of the argument follows that of Durnev et al. (2004). We compute the measure of price informativeness $\left(1 - R_{it}^2\right)/R_{it}^2$ for each stock i on date t using the S&P500 exchange-traded fund (SPY) as the market index and considering 15-minute intervals during the trading day. Because of infrequent trades (a concern especially before 2001), we average prices over two minutes for each national BBO (NBBO) quote, for example, averaging over 9:59 a.m.–10:01 a.m. for 10 a.m.

Volume-based Signals.

Easley and O'Hara (1992) pioneered the role of volume as a measure of adverse selection. In contrast to Glosten and Milgrom (1985) and Kyle (1985), liquidity providers in this model need to learn not only about the sign of private information but also about the occurrence of private information. Given that liquidity (noise) traders have perfectly inelastic demands, volume in this model is higher when there is an information event. Based on this notion, Easley et al. (1996b; 1996a) develop the PIN measure, which aims to capture the adverse selection risk faced by uninformed traders.[8] We follow Easley et al. (2008) and use the absolute order imbalance as a proxy for the PIN, which has

[8] Banerjee and Green (2015) further argue that the relation between the occurrence of information events and the PIN may not be monotonic. When uninformed traders place a very high (low) likelihood on informed traders being present, they know that the price is informative (uninformative) about fundamentals and the asymmetric information problem is mitigated.

two distinct advantages: First, it can be computed over short periods, such as a day. Second, it does not have the numerical overflow problems that can arise when computing the PIN log-likelihood function.

Below, we formally define all volume-based signals.

Absolute Order Imbalance. The absolute order imbalance is defined as

$$AOI_{s,t} = \left| \frac{Buys_t - Sells_t}{Buys_t + Sells_t} \right|,$$

where $Buys_t$ and $Sells_t$ are the numbers of buys and sells, respectively, over a given trading day t.

Abnormal Volume in Stocks. We compute abnormal volume in stocks as

$$\text{Abnormal Volume}_{s,t} = \text{Volume}_{s,t} - \text{Predicted Volume}_{s,t},$$

where total volume is the total trading stock volume on day t. The variable Predicted Volume is computed using a linear regression model with the total volume as a dependent variable and the following contemporaneous controls: median daily cross-sectional volume of all stocks, the Chicago Board Options Exchange Volatility Index (VIX), the excess return of the value-weighted market portfolio, and the daily stock return.[9]

Price- and Volume-Based Signals.

The imperfect competition model of Kyle (1985) predicts that the presence of a single informed trader should induce prices to react to the order flow imbalance. Adverse selection thus increases the price impact sensitivity, or lambda. More generally, the speed at which prices reflect information naturally depends on the number of informed traders (e.g., Holden and Subrahmanyam, 1992; Foster and Viswanathan, 1996; Back, Cao, and Willard, 2000). Trading volume and returns are also related in Wang's (1994) model with risk-averse agents. As information asymmetry increases, uninformed investors demand a larger price discount when they buy the stock from informed investors

[9]The predictive model's coefficients are computed over a time window of [-55,-15] trading days prior to the informed trade.

to cover the risk of trading against private information. Therefore, the trading volume is positively correlated with absolute price changes and this correlation becomes stronger with greater information asymmetry. We consider two empirical measures that combine price and volume information in the spirit of Kyle's lambda: lambda and the daily illiquidity measure.

Lambda. We follow Hasbrouck (2009) and Goyenko et al. (2009) and compute lambda as the slope coefficient in the following regression:

$$\text{Lambda}_{s,t} \text{ (slope): } r_n = \lambda \times (\sum_k d_k \sqrt{|vol_k|})_n + \text{error}_n$$

where, for the n-th time interval period on date t, r_n is the stock return, vol_k is transaction k-th's dollar volume, and the bracketed term represents the signed volume over interval n. Intuitively, the slope of the regression measures the cost of demanding a certain amount of liquidity over a given time period. We report the results based on five-minute intervals.[10]

Illiquidity. For a given day t, it is given by the ratio between the absolute price return to dollar volume

$$\text{Illiquidity}_{s,t} = \frac{|r_{s,t}|}{\text{Volume}_{s,t}}.$$

Intuitively, a liquid stock is one that experiences small price changes per unit of trading volume. Naturally, Amihud's (2002) *ILLIQ* can be seen as a monthly average of the daily measure.

2.2 Private Information in Option Markets

Privately informed agents can also consider option markets. Black (1975) was the first to suggest that options might play an important role in price discovery, because informed traders should prefer options to stocks due to their embedded leverage. Although several of the insights from Section 2.1 are also useful in the analysis of options, we further consider insights from a (relatively scant) literature that has explicitly considered equilibrium models of informed trading in option markets. In these models, asymmetric information violates the assumptions underlying complete markets and, therefore, the option trading process is not redundant.

[10] We also computed Lambda and the realized variance based on 30-minute intervals, obtaining similar results.

Price-Based Signals.

Easley et al. (1998) study a sequential trade model à la Glosten–Milgrom in which investors can trade a single unit of the underlying (with a binary payoff), a put, or a call option with a competitive market maker who sets bid and ask prices. The authors find that, consistent with economic intuition, asymmetric information increases options' bid–ask spreads.

Less obvious is the effect of asymmetric information on IV. Suppose an informed trader receives good news about a firm. At face value, if the trader increases total demand for, say, call options, the associated IV will increase. However, this simple connection does not take into account how uninformed traders will react in equilibrium (Biais and Hillion, 1994). Vanden (2008) studies a more sophisticated environment in which the quality of information varies and finds that option values are decreasing in information quality. If one interprets the arrival of material inside information as increasing information quality, the effect could then play in a direction opposite to simple intuition. The complex relation between private information and option value motivates us to consider an additional measures of IV, the IV Spread, which measures the average difference in IVs between call and put options with the same strike price and expiration date. One would expect an insider with positive news to buy the call option, possibly to sell the put option, or to do both. In such case, the IV difference between calls and puts would widen. Consistent with this intuition, Cremers and Weinbaum (2010) show that high values of the IV Spread are associated with a positive abnormal performance of the underlying stock.

Formally, we define the price-based option signals as follows. In all cases, the weighting factor ω_j corresponds to the the open-interest weight of option j.

Option Quoted Spread. Let t and i index trading dates and underlying stocks, respectively. Let $j = 1, ..., J$ denote a strike-maturity combination for calls and puts on the same underlying stock. The daily quoted bid–ask spread is defined as

$$\text{Quoted Spread}_{o,t}{=}\textstyle\sum_{j=1:J} \omega_j \left(\frac{a_{jt}-b_{jt}}{m_{jt}}\right),$$

where the quotes correspond to values at the end of the day. We also consider a version that concentrates on highly levered (out-of-the-money, or OTM) options (QS_{otm}).

IV (IV_c and IV_p). For both calls and puts, the daily IV is computed as an open–interest-weighted average of OptionMetrics' IVs, respectively:

$$IV_{c,t}=\sum_{j=1:J}\omega_j OMIV_j^{CALL},$$
$$IV_{p,t}=\sum_{j=1:J}\omega_j OMIV_j^{PUT}.$$

IV Skew. Following Cremers and Weinbaum (2010), we compute the IVS measure for a given underlying stock on a given day t as

$$IVS_t=\sum_{j=1:J}\omega_j\left|OMIV_j^{CALL}-OMIV_j^{PUT}\right|.$$

Only pairs with IV and open interest records are included in the calculation.

Volume-Based Signals.

Back (1993) introduces trading in a single at-the-money (ATM) call option into a continuous-time version of Kyle (1985) with a single privately informed trader. Back shows that the introduction of option trading can cause the volatility of the underlying asset to become stochastic and, importantly for our purposes, that option volume is not redundant and that it can affect stock prices. Easley et al. (1998) study a sequential trade model in which investors can trade a single unit of the underlying (with a binary payoff), a put, or a call option with a competitive market maker who sets bid and ask prices. They find that option volume has an informational role and can move stock prices. A limitation of the equilibrium option trading models cited is that they rely on non-strategic liquidity traders. Thus, liquidity and volume purely depend on the interaction between the informed trader and market makers. In contrast, Biais and Hillion (1994) consider a single-period model of insider trading in an incomplete market. They assume that the asset payoff takes only three values and hence a single option is sufficient to complete the market. In contrast with the study of Back (1993), for example, the good news–informed trader may not buy the OTM option, given that liquidity traders are strategic and may not trade this option.

We formally define the volume-based option signals as follows.[11]

Abnormal Volume in Options. We follow Augustin et al. (2015) and compute a measure of abnormal volume in options. For all active contracts in a given underlying company, we calculate

$$\text{Abnormal Volume}_{o,t} = \text{Volume}_{o,t} - \text{Predicted Volume}_{o,t},$$

where Volume is the number of traded contracts on day t and Predicted Volume is computed using a linear regression model with the total volume for the same underlying and the following contemporaneous controls: the median volume in all equity options, the VIX, the excess return of the value-weighted market portfolio, and the daily return of the underlying stock.[12]

Volume Ratio otm/all. Based on Black's (1975) insight that informed traders value leverage, we compute the ratio of the volume in OTM options to the non-OTM volume. Naturally, if informed traders value leverage, a high signal value could indicate informed trading. Specifically, for all options with the same underlying stock, we have

$$\text{Volume Ratio}_{otm|all,t} = \frac{\text{OTM Volume}_t}{\text{(ITM+ATM) Volume}_t}.$$

In cases in which the denominator (but not the numerator) is equal to zero, we set the value of VR_{otm} to 100 (the 99th percentile of the empirical distribution).

2.3 Mixed-Market Signals

Motivated by the theoretical literature in Sections 2.1 and 2.2, we propose a number of signals that are based on a combination of stock and option data.

Quoted Spread Ratio. We study whether the informed trade effect in bid–ask spreads is proportionally larger in the option or stock market by computing the ratio Quoted Spread$_o$/Quoted Spread$_s$.

Volume Ratios (VR). Roll, Schwartz, and Subrahmanyam (2010) conjecture that private information could increase the value of the option volume relative to the volume in the underlying.

[11] We do not compute the PIN or Absolute Order Imbalance for options, since OptionMetrics does not provide intraday trades. Easley et al. (1998), however, argue against the use of the PIN in option markets.

[12] The predictive model coefficients are computed over a time window of [-55,-15] trading days prior to the informed trade.

Johnson and So (2016) formalize this idea using a simple model of trading with different assets. They show, theoretically, that episodes of information-motivated trades should display higher values of the option to stock volume (O/S).[13] Formally, the option stock volume ratio is given by

$$\text{Volume Ratio}_{o|s,t} = \frac{\text{Option Volume}_t}{\text{Underlying Stock Volume}_t}.$$

The option volume includes the total volume in the call and put options of all strikes and all maturities from OptionMetrics. We also consider $VR_{c|s}$ and $VR_{p|s}$, which are computed using the call and put options volumes in the numerator, respectively.

Illiquidity Ratios. Easley et al. (1998) find that option volume has an informational role and can move stock prices. To capture this effect, we extend the reach of the illiquidity measure to account for cross-market interactions. In particular, the illiquidity *stock-to-option* signal is defined as

$$\text{Illiq}_{s|o,t}{=}\frac{|Stock\ Return_t|}{Option\ Volume_t},$$

where *Option Volume* accounts for the volume on dat t in all options of the same underlying. We propose a second signal that, analogously, captures the interaction between stock volume and option returns. In particular, the illiquidity *option-to-stock* signal is defined as

$$\text{Illiq}_{o|s,t}{=}\frac{|Option\ Return_t|}{Stock\ Volume_t},$$

where the variable Option Return is computed as the percentage daily change in the IV of a particular contract. We believe this is a reasonable approximation to option returns over a short period of one trading day.

[13] Johnson and So (2012) develop a model with short-selling constraints and argue that, because of these constraints, high values of O/S negatively predict future returns. This is because informed traders use options more often when negative news arrives. One advantage of our setting is that we can observe the sign of information directly. As shown in Section 4, our O/S results are indeed stronger for positive news.

2.4 Public Trade Data and Implementation Details

Altogether, our signals span the period of 1995–2015 and are recorded at a daily frequency. Table II reports basic summary statistics. Stock-based signals based on high- and low-frequency data are computed using monthly Trade and Quote (TAQ) and Center for Research in Security Prices (CRSP) data, respectively. We compute the intra-day NBBO prices for each stock using the interpolated time method of Holden et al. (2014). In addition to dollar-weighted averages, we also computed intraday stock-based signals using the number of shares as weights, obtaining similar results. We consider alternative trade-typing conventions to determine whether a given trade is sell or buy initiated. For brevity, we report the results using the Lee–Ready algorithm (1991) only. We obtain option data from the Ivy DB OptionMetrics database, which provides end-of-day information for all exchanged-listed options on U.S. stocks, including option prices, volumes, and IVs. All signals are winsorized at the 1% level to mitigate the influence of outliers.

3 Insider Trading Sample

3.1 Background

The term *insider trading* refers to both legal and illegal conduct. The legal variety is when corporate insiders—officers, directors, large shareholders, and employees—buy and sell stock in their own companies and report their trades to the SEC. On the other hand, illegal insider trading refers to buying or selling a security in breach of a fiduciary duty or other relationship of trust and confidence, while in possession of material, nonpublic information about the security.

The legal framework prohibiting insider trading was established by Rule 10b-5 of the Securities Exchange Act of 1934. Under the classical view of insider trading, a trader violates Rule 10b-5 if trading on material, nonpublic information about a firm to which the trader owes a fiduciary duty, where information is deemed material if a reasonable investor would consider it important in deciding whether to buy or sell securities. Alternative interpretations of what constitutes illegal insider trading activity continue to be made to this day. We do not seek to settle this debate in this paper. In fact, whether a given trade is technically illegal or not is not important for us. Rather, our identification strategy relies on two conditions: (i) The considered trade was motivated by actual information, as opposed to, say, sentiment, and (ii) the material information was not widely available to market participants at the time of the trade. This approach allows us to concentrate on all investigations for which the SEC reported that conditions (i) and (ii) were met, regardless of the legal resolution of the case.[14]

3.2 Data Collection

We retrieve the list of SEC investigations from all SEC press releases that contain the term *insider trading*. We use this list to obtain all the available civil complaint files available on the SEC website. In cases whose complaint file is not available on the SEC website, we rely on manual web searches and on information from the U.S. District Court where the case is filed. We collect all files starting from January 2001 until December 2015. We track all documents that provide updates on a previously released legal case. Whenever updated information is made available at a later date, we rely on the most recent version.

The resulting sample represents all SEC cases that were either litigated or settled out of court. Most complaint files include a detailed account of the allegations. Since the documents provide most of the relevant information in textual form, the data files must be thoroughly read and summarized by hand. Available information typically includes the biographical records of defendants, individual trades, a description of the leak that the trades are linked to, and the relationships between tippers and tippees.

We organize the information by characterizing trades and information events. A *trade* is any single transaction record for which we can observe a date and a trading instrument (e.g., stock or options). For most trades, information about the price, trade direction, quantity, trading profits, and the closing date of the position are also available, as well as contract characteristics for options. Whenever only a date range is available, we only consider as trading dates the first and the last days of the range. This condition reduces the potential number of trading dates but yields well-identified

[14]Furthermore, the legal resolution for a significant proportion of investigations is a monetary settlement with the SEC. It is difficult to infer from such resolutions whether the defendant is guilty or would rather pay a fine than legally contest the regulator.

trading date records throughout the analysis. We also record individual names in cases in which more than one person/firm executed a trade on a single piece of news.

An *information event* is a collection of one or more trades that were motivated by a unique piece of private information, such as an earnings announcement or a merger. For our purpose, the key information event records include the firms involved, the nature of the leaked information (e.g., a new product), and the date at which the information was released to the general public. We also collect information on the date of information transmission from tipper to tippee. This information allows us to test hypotheses on strategic trading delays.

3.3 Descriptive Statistics

Our data cover 453 legal cases. The most frequent event types are M&As (55.90%), followed by earnings announcements (15.06%). The business events and corporate events categories (10.71%) include, among others, items such as information about products, a firm's projects, patents, FDA medical trials, corporate restructuring, bankruptcy, and fraud. The average number of cases per year in our sample is 30.83, with a maximum of cases (46) filed in 2012. The distribution of the number of firms per case is highly asymmetric. Approximately 80% of the cases involve a single firm, while 4% of the cases involve 10 firms or more.

In Table III, we summarize our data at the trade level, which is our main unit of observation. We identify a total of 5,058 unique trades involving 615 firms. In Panel A, we show the distribution of trades with respect to the trading instrument. The vast majority of trades are executed via stocks (67.06%) and options (31.83%). The remaining few are trades in American depositary shares and bonds. In Panel B, we show the breakdown of trades with regard to the trade direction. There are 4,220 buys (83.43%) and 838 sells. In Panel C, we present the distribution of trades by year. Notably, even though our legal cases date back to 2001, several cases involve trades that took place earlier on. Consequently, our sample of trades spans a longer time period, 1995–2015. The sample is quite evenly distributed over time, with over 100 trades in each year between 1999 and 2014. We observe a smaller number of trades in the 1990s and again toward the end of our sample, in 2015. The latter situation is explained by the delay with which cases can be identified and formally prepared by the SEC. The observed dispersion of trades across years is an attractive feature of our data that allows us to address common identification issues, such as time-specific macro events, etc.

In Panel D of Table III, we consider the distribution of trades with respect to the primary industry classification of a traded company. Our definition of industry is based on the two-digit SIC code. The distribution of trades is highly dispersed across many different industries. The three most represented industry sectors in our sample are chemicals, business services, and electronic equipment, which account for more than 40% of all trades. However, we note that the trading involves companies coming from almost all industrial sectors. Finally, in Panel E, we provide a set of different statistics on the characteristics of the trades and trading parties. The median time between the arrival and the use of information by insiders is two days. In turn, the median number of days from a trade till an information event is seven days. The majority of cases involve single trades in a given company, but a subset of traders execute more than one trade. The median horizon between the first and the last such trade is eight days. Further, a median trader in our sample executes 10 trades, with a maximum of 97 trades. A median firm receives 16 trades and a median legal case involves two firms. The median age of tippers and traders is almost identical and equals 45 years. The vast majority of tippers and traders in our sample are male. The profits reported by traders are highly skewed, with an average trade profit of $1.01 million and the median of $90,000, and 49% of trades elicit at least $100,000 in profits.

3.4 How Much Private Information?

Our empirical design relies on the work by the SEC to verify the material and non-public nature of information. Naturally, an interesting issue arises: How 'material' is the information received? In other words, how strong is its information content? To shed light on this aspect, for each information event, we compute the percentage change in the corresponding stock price from the open of the day of the informed trade to the open price immediately after the information becomes public. For example, if information about earnings is disclosed overnight on date t, we consider the open price on date $t + 1$. Table IV shows the results for each type of news and the aggregate sample. For positive news, the average return is greater than 43.5% and the median return is approximately 33.7%. These values are remarkably large, given that the median time interval from a trade to private information disclosure is a mere seven days. Moreover, one could treat these numbers as a lower bound on the true signal strength, since about 30% of trades are in options, hence embedding leverage. To put these numbers in another perspective, we construct benchmark returns for a sample of SEC 13D form filers between 1994 and 2014. The benchmark return is based on the return measured from the opening of the day when the 13D filer trades an asset until the opening of the day following the release of the trade information to the public. The trades of 13D filers represent large long positions in a security and have been shown to predict positive stock returns, so they can be interpreted as based on positive news (e.g., Brav, Jiang, and Kim, 2015; Collin-Dufresne and Fos, 2015). The mean and median returns for 13D filers are 4.9% and 2.4%, respectively.

3.5 Economic Significance

A relevant question is whether our sample of insider traders and their trades is economically significant. We assess this issue in two ways. First, we analyze the background of insiders in our sample. We find that at least 60% of them have some finance background or work for financial firms and 30% of them are highly-ranked corporate executives (vice-president level or higher). Hence, they are likely to be skilled investors capable of sophisticated trading. Second, we evaluate the scope of trading done by the insiders on the days when they trade by aggregating all trades in a given firm on that day. We do so separately for stocks and for options. Our results in Table V show that the insider trades make up a significant percentage of total trades in the market. On average, 10% of the daily volume in stocks and more than 30% of the option volume are traded by insiders. In summary, we argue that our sample can be interpreted within a rather broad economic context.

4 Evidence from Illegal Insider Trading

4.1 Empirical Design

Our analysis utilizes a setting in which we can observe the use of private information for a given company on a given day. We hypothesize that, if firm-specific signals capture the presence of private information, they should display abnormal behavior on days when privately informed traders are present. Using equation (1), we thus consider a null hypothesis where $\Delta = 0$ against the alternative hypothesis where $\Delta \neq 0$. To implement the main empirical test, we consider an event study analysis where we compare the value of a given information signal on event days, defined by insiders' trades on a specific firm, and a control time window representing "normal" signal behavior. We observe events that are staggered over time and across many firms, which helps to ensure that our results are not explained by any time trends or individual firm effects. The underlying identifying condition is standard in the literature (e.g., the PIN model): For any given asset, privately informed traders are not present every single trading date and thus the probability of informed trading on any random date is less than one.

We select a control time period spanning 21–35 trading days before the informed trade. We focus on a narrow event window, which insulates us from any longer-term trends driving the data. Skipping the last 20 days in the pre-event window is likely to eliminate any serial correlation or abnormality around the event date.[15] A trader (or a group of traders) could trade a given firm more than once on a given day, because they wither split their trades or because they use different trading instruments. To avoid double counting, we include only one daily observation and the corresponding pre-event window. Further, some traders trade over a sequence of days. While we count each day as a separate observation, we use only the pre-event window that corresponds to the earliest of the trades. In sum, our observations are uniquely defined at a firm/time level. Lastly, we eliminate all cases in which the insider trades happen less than four days prior to a scheduled corporate event announcement. This restriction makes it more plausible that other traders' trades prior to or on

[15] We evaluated alternative event window specifications and plotted the time series of information signals around scheduled and unscheduled announcements. The values in the [-21,-35] pre-event window are stable and do not exhibit hardly any serial correlation or time trend.

the event date are not motivated by directional bets on the announcement.[16] Figure 1 summarizes the construction of the control window.

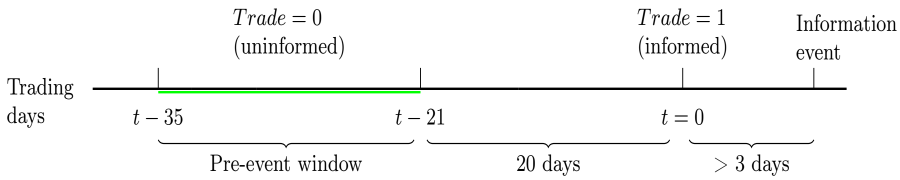


Figure 1. Event Study Time Line

We consider two basic regression specifications to conduct the test. First, we estimate the following multivariate regression model:

$$IS_{it} = b + \Delta\times\text{InfoTrade}_i+c\times\text{Controls}_{it}+\text{d}_i+\ \text{e}_t+\ \epsilon_{it}, \tag{2}$$

where $IS_{i,t}$ is the information signal for company i measured at time t, InfoTrade is an indicator variable equal to one on the day in which a company is traded by insiders and zero over the control window, and Controls is a vector of firm-specific controls, including $LNSIZE$, $LNVOL$, $TURNOVER$, and the equity price per share (PRC). Throughout all models, we winsorize all IS measures at the 1% level. To account for the possibility of information signals and controls varying generically over time and across firms, we also include firm and time fixed effects.

Our second and main model is a simple difference-in-differences specification in which we compare each firm involved in insider trading (treatment group) to a matched portfolio of firms (control group) with similar characteristics. Our control portfolio is composed of firms that belong to the same two-digit SIC industry and the same market capitalization quintile. Subsequently, we calculate the arithmetic average of a given information signal in the portfolio and subtract it from the information signal, which results in a control-adjusted information signal ($CAIS$). The construction of our estimation window follows the same principles as before, and the difference-in-differences estimation is equivalent to estimating a regression model in (2), except that we replace IS with $CAIS$:

[16]When we plot the time series of signals around all scheduled corporate announcement, we observe that some of them (e.g., option's IVs) systematically increase a few days prior. Although removing the three-day exclusion period does not change our results qualitatively, it could downwardly bias the estimated value of Δ.

$$CAIS_{it} = b + \Delta\times\text{InfoTrade}_{it,t-k} + c\times\text{Controls}_{it} + \text{d}_i + \text{e}_t + \epsilon_{it}. \tag{3}$$

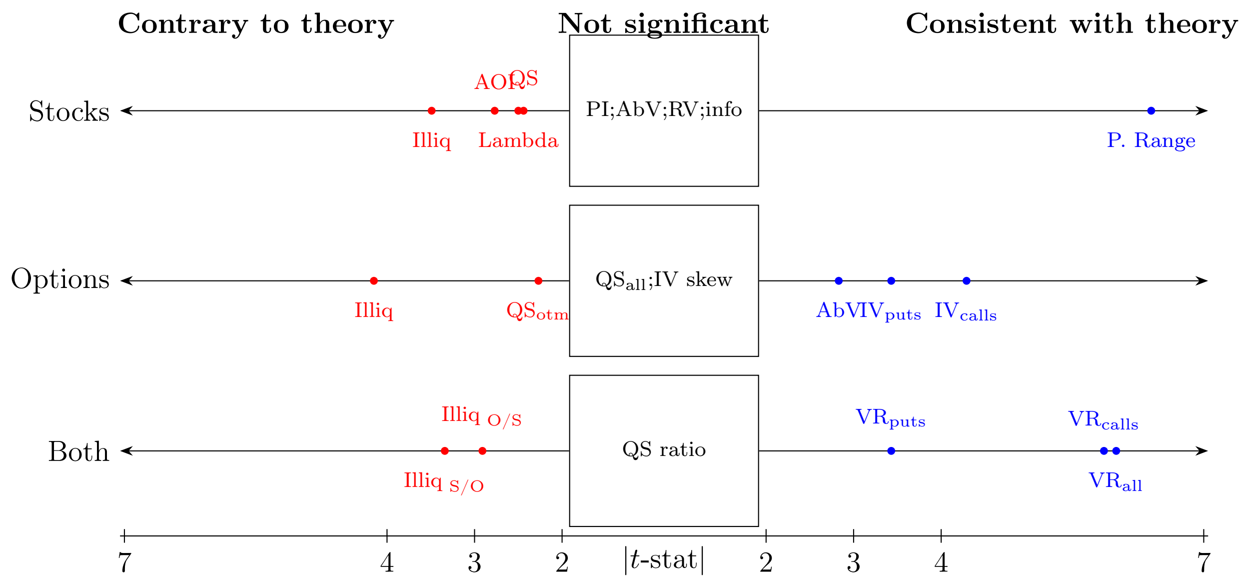
4.2 Baseline Results

In Table VI, we present the results from estimating the regression model for stock-based signals. In Panel A, we estimate a model with *InfoTrade* and basic controls. Of the nine considered signals, eight are statistically significantly different on event days. Notably, five of the coefficients have a negative sign, generally suggesting that liquidity (price impact) is higher (lower) on the informed trading day. In Panel B, we additionally introduce firm fixed effects to account for the possibility that information signals and firm characteristics vary across firms, thus rendering any comparisons difficult. We also include time fixed effects to account for the possibility that the signals are time varying. We find that the coefficients are generally consistent with those in Panel A. Finally, in Panel C, we replace IS in Panel B with control-adjusted information signals, $CAIS$. In this test, six coefficients remain statistically significant. We note that their magnitudes of the coefficients do not vary much between Panels B and C, which suggests that our treatment effect might be fairly independent of other firm- and time-specific observables. In summary, while several coefficients for stock-based signals are statistically significant, only one, the price range, conforms to standard theories of trading with private information.

Panels A to C of Table VII present the results for option-based information signals. Of the eight signals we analyze, five have significant coefficients for InfoTrade in Panel A. The most significant coefficients are for abnormal volume and illiquidity; however, the latter one is negative. The greater liquidity on days of insider trading is consistent with the results for stock-based measure of liquidity. When we further account for fixed effects, we observe that the coefficients of IV are positive and statistically related to InfoTrade. In contrast, we find that the quoted spread (especially on OTM contracts) is negatively related to InfoTrade. Overall, our results display a strong positive relationship for abnormal volumes and IV, as implied by theory, but a negative relationship for quoted spreads and illiquidity.

Finally, we perform the baseline test for mixed-market signals and report the results in Table

Figure 2. Main Empirical Design: Results Summary



VIII (Panels A–C). We observe the most consistent patterns for signals that rely on the ratio of options (all options, calls, puts, or OTM options) to stock volume. These ratios are positive and statistically significant for all four specifications we consider. Similarly, we find a strong and negative effect for measures of illiquidity based on cross-market volumes and absolute returns. The ratio of quoted spreads between options and the underlying stock does not change significantly.

Figure 2 provides a summary of our baseline results by graphically displaying, for each market, the signal-specific t-statistic values corresponding to the coefficients in Tables VI to VIII. First and foremost, taken together, our results indicate that information signals *do* display abnormal behavior on days with trades motivated by private information about firm fundamentals. Second, several measures, notably liquidity metrics in the stock and option markets, behave in an unexpected fashion in light of standard theories. Third, there are both similarities and differences across markets. Volatility-based signals, such as IV, for calls and puts, display higher values in option markets, as well as a higher Price Range in stock markets. However, we identify information-related abnormal volumes only for options. The relation between option and stock volumes seems to provide a stronger signal of informed trading than stand-alone option volumes.

4.3 The Sensitivity to Trading Intensity

The evidence in Section 4.2 suggests that information signals display different behaviors on days when privately informed traders trade. It is then natural to hypothesize that a larger share of insider trading has a greater impact on such signals and thus be more indicative of information-driven trades. To further explore this connection, we split both stock and option trades into low-intensity (high-intensity) trades if the respective insider trades are below (above) the within-asset median. We then estimate the regression model in (3) for all information signals conditional on low- and high-intensity trades. Table IX displays the results. Overall, the qualitative results from high-intensity trades are not very different from those for the unconditional sample. Some information signals are only significant for high-intensity cases: the abnormal order imbalance and illiquidity in stock markets and IV for calls in option markets. The associated t-statistic values are generally higher for high-intensity cases in all equity, option, and mixed-market cases. These observations are consistent with the view that a larger insider trading share has a greater impact on the informativeness of signals.

5 Empirical Identification

One could argue that, in its decision to launch an investigation, the SEC could screen trades based on the signals we find informative. One would then be concerned about sample selection bias. This concern would be particularly strong if insider traders were exposed *only* when these signals display abnormal values. If that were the case, one could then overestimate the signals' capacity to detect information. Our analysis does not support this view. First, many stock-based signals display patterns that are generally inconsistent with what economic reasoning would suggest are patterns of informed trading. For example, daily illiquidity systematically takes a lower value on days with informed trades. One would then need to believe that the SEC is particularly sensitive to criminal activity when markets look orderly and abnormally liquid. Second, prior evidence suggests that a significant fraction of investigations originate from external tips. Meulbroek (1992) studies a sample of cases filed by the SEC in the 1980s and reports that "public complaints," a category of investigations initiated for reasons unrelated to direct screening by regulators, are the most important source of investigations (41% of cases). Another important source of tipping is from third parties, such as exchanges or brokers observing "suspicious" portfolio activity in their clients' accounts. A typical situation in this case is for an individual to buy a large position in a company for the first time just before a merger or important corporate announcement. This second category is naturally more likely to be based on actual trades, but relies on access to traders' identities, a source of information that is non-public. Indeed, even if the regulating agency intended to rely on public information based on an aggregation of trades (e.g., liquidity measures), it is unlikely that officials would be able to identify a specific individual breaching the law. This notion is supported by interviews we conducted with SEC officials.

Last and most important, we provide four independent sets of results—from the SEC Whistleblower Reward Program, case complexity, signal strength, and placebo test—that largely suggest that the selection issues related to the SEC screening its cases based on the dynamic features of signals we analyze are unlikely to bias our results. At the same time, we do not necessarily argue that other selection criteria do not affect the SEC's decision to pursue investigations (e.g., whether the evidence against an investor is reliable or whether he or she breached a fiduciary duty to a particular firm). What is relevant to us is that this decision is orthogonal to the dynamics of our information signals.

5.1 Evidence from the SEC Whistleblower Reward Program

The first and arguably the most convincing test we conduct relies on the regulatory environment of insider trading investigations. As part of the Dodd–Frank Act of 2010 (15 USC par. 78u-6), the SEC instituted the Whistleblower Reward Program. The underlying idea of the program is to reward whistleblowers for providing *original information* directly to the SEC or related agencies. The program defines original information as one that is 1) derived from the independent knowledge or analysis of a whistleblower, 2) not known to the SEC from any other sources, and 3) not exclusively derived from an allegation made in a judicial or administrative hearing, governmental report, hearing, audit, or investigation or from the news media. This definition makes it clear that the detection of such cases is uncorrelated with any SEC/government action and thus such cases are free of selection concerns based on our information signals. Hence, if selection bias drives our results, we would expect that our signals display different dynamics for cases originating from the program than for any other cases, whose investigation origins might be less independent.

Since the Whistleblower Reward Program was implemented in 2011, for symmetry, we limit our analysis to cases that were filed during the period of 2011–2015. Our sample thus includes 166 different cases, 37 of which were investigated through the program and 129 of which do not have a precise source of investigation (could be the result of SEC analyses or based on independent tips). In Table X, we summarize various trading characteristics for the two types of cases. We note that the two sets of cases are not very different from each other along most of the trading dimensions. The only notable difference is that the Whistleblower Reward Program cases involve, on average, companies with greater market capitalization. Hence, it seems that the source of investigation does not seem to introduce a particular bias in terms of trading behavior.

Next, we test whether the ability of information signals to detect private information depends on the source of investigation. To this end, we estimate a modified version of the regression model in equation (3):

$$\begin{aligned} CAIS_{it} = a + b\times\text{InfoTrade}_{it,t-k} + c \times WB_{it,t-k} + d\times\text{InfoTrade}_{it,t-k}\times\text{WB}_{it,t-k} \\ + e \times \text{Controls}_{it} + f_i + g_t + \epsilon_{it}, \end{aligned} \tag{4}$$

where WB is an indicator variable equal to one if a trade is part of a case investigated through the whistleblower program and zero if it is investigated based on other sources. The coefficient of interest is *d,* which measures the differential impact of whistleblower cases relative to other cases. We present the results in Table XI. Panel A shows the results for stock-based signals. We find no statistically significant difference across the two subsamples for seven out of nine signals. The only statistical difference is the positive coefficient of the interaction term for *Lambda* and *Illiquidity*, which implies a negative relation for whistleblower-based trades and no relation for other trades.

Given that one would worry about the selection of these other cases this result makes it even less likely that the behavior of such signal would be picked up by the SEC as suspicious. In Panel B, we report no significant differences for the option-based signals. Finally, Panel C indicates a significant result only for one mixed-market signal (*VR* for puts).

Altogether, given the *as-if-random* nature of our test, our results suggest that the selection based on abnormal variation in information signals is unlikely to explain our results. Assuming that a similar selection process underlies pre-2011 cases, we can argue that the selection concern is unlikely to explain all the cases we study.

5.2 Evidence from Case Complexity

Another identification idea we pursue is based on the nature of the cases we analyze and is similar in spirit to that used by Meulbroek (1992). Specifically, an important proportion of SEC investigations, which we label simple, involve only one or two companies. Others, that we label as complex, involve a greater number of firms (up to 25 different firms in the sample). It is reasonable to expect that the probability that the investigation trigger is related to an abnormal trading pattern is greater for simple cases than it is for complex cases. Intuitively, for a generic case involving, say, 10 firms, it is unlikely that insider trade was detected based on independent publicly observed price or volume movements in *each* firm. Rather, even when the investigation originated from screening one firm's *IS* values, it is likely that trades in subsequent firms were uncovered as part of an ongoing investigation (e.g., involving access to individual brokerage accounts, phone conversations). Consequently, if selection bias drives our results, one should expect the informativeness of signals to be greater for simple cases.

Next, we estimate the following regression model for the entire sample of cases:

$$
\begin{aligned}
CAIS_{it} = a + b \times \text{InfoTrade}_{it,t-k} + c \times \text{SIMPLE}_{it,t-k} + d \times \text{InfoTrade}_{it,t-k} \times \text{SIMPLE}_{it,t-k} \\
+ e \times \text{Controls}_{it} + f_i + g_t + \epsilon_{it}, \qquad (5)
\end{aligned}
$$

where *SIMPLE* is an indicator variable equal to one if the trade is collected from a simple case and zero if it is collected from a complex case. The coefficient of interest is *d,* which measures the differential behavior of signals for trades obtained from simple cases relative to those obtained from complex cases. The results are reported in Table A1 of the Online Appendix. We find no significant differences in the impact of informed trading for 20 out of 22 information signals. The only exceptions are *Lambda* and *Abnormal Option Volume*. Hence, we can conclude that the ease with which the SEC could potentially identify informed trading does not affect the informativeness of our information signals.

5.3 Evidence from Signal Strength

In our third test, we assess whether the behavior of information signals is correlated to the profitability of trades in each investigation. Such correlation could indicate that the SEC selects cases that are distinctly profitable, a potential source of inference bias. To evaluate this hypothesis formally, we define a variable *Strength* that measures the ex post profits generated from a given trade. Subsequently, we estimate the regression model in (3) with the interaction term of *Strength* and InfoTrade as the main variable of interest. Naturally, if the profitability of individual trades has some kind of monotonic effect on the response of information signals, the interaction term should be statistically significant. The estimation results shown in Table A2 of the Online Appendix suggest the opposite. Virtually all the information signals considered display a statistically insignificant interaction term. Hence, even if the SEC screens cases based on their profitability, that selection does not seem to correlate much with the results we document.

5.4 Evidence from Tipping Events

Our empirical analysis likely considers only a subset of informed trades. Thus, one could ask whether the dynamics of signals we observe could be confounded with other dates at which other possible insiders trade. Even though our control sample seems to rule it out indirectly, a more direct approach would be to look for another date as a period of likely insider trading. A natural candidate is the date at which information is originally passed on by tippers to insiders from our sample. To the extent that other (undetected) market participants may trade prior to our modeled insiders, the question is whether similar patterns can be observed in this placebo test.

Formally, we construct an alternative indicator variable InfoRec that equals one on the date in which the insider received the tip and zero for the period of 35 to 21 trading days preceding this event. We then follow a similar approach to that in (3) except that we replace InfoTrade by InfoRec. We exclude from our test all events whose date when information is passed on to the insider is identical to the date when the insider trades. We present the results from the placebo tests in Table XII: Panel A for stock-based signals, Panel B for option-based signals, and Panel C for mixed-market signals. Across all specifications, we find a weak statistical relationship between *InfoRec* and the informed trading signals. Only one signal, option illiquidity, is strongly negatively related to *InfoRec*.

6 Cross-Sectional Tests and Option Contracts

6.1 Cross-Sectional Tests

In this section, we present additional cross-sectional tests to shed light on the economics of information transmission in financial markets. We discuss differences across trader expertise as well as the type of and sign of the information that they received.

Insider Financial Expertise. An interesting issue is whether trader skill or expertise affects the relation between trades and information signal behavior. Two distinctive features of our data are the ability to identify individual traders and a great deal of heterogeneity in backgrounds and professions. While some of the insider traders are professional investors, others are individuals with no direct connection to the finance sector and possibly less sophisticated trading behavior. For simplicity, we group traders into two groups according to whether they are likely to have high trading expertise. We assign high expertise to traders with finance-related jobs (e.g., professional traders, brokers, chief financial officers) or to those who hold top executive positions, that is, vice-president or a higher corporate rank (e.g., chief executive officers, chief operating officers, board members). Under this classification, high-expertise individuals constitute about 51% of all traders in our sample.

The impact of high expertise is, in principle, not obvious. On the one hand, sophisticated investors could trade larger orders and induce a stronger response of information signals. On the other hand, we hypothesize that high-expertise traders could use more elaborate trading strategic designed to make their identification by regulators or exchanges more difficult.

To assess the impact of trading expertise, we estimate the regression model in (3) for all information signals, separately for high- and low-expertise traders. Table XIII presents the regression results and Panel (b) of Figure 4 graphically displays the associated t-statistic values for each signal. Interestingly, across most signals, we observe that the coefficient of InfoTrade becomes smaller and less significant for the sample of high-expertise trades, consistent with the prediction that such trades are better disguised from the public. Abnormal volume, for example, is only statistically significant for low-expertise traders, in both stock and option markets.

Corporate Event Types. In this section, we examine whether the behavior of information signals depends on the particular event category. In particular, we distinguish between scheduled events, earnings announcements, and unscheduled events, M&As. This distinction is relevant to an empirical test of informed trading, given that scheduled announcements could have investors taking directional bets on the event outcome, even when they do not act on actual information but, instead, the sentiment or belief that they are informed. To this end, we estimate the regression model in (3) for stock-based, option-based, and mixed-market information signals as dependent variables separately for mergers and earnings events. The regression results are presented in Table A3 of the Online Appendix and summarized in Panel (c) of Figure 4.

For stock-based signals, we observe that the unconditional results discussed in Section 4 are largely mirrored by those for the M&A sample: Price Range is positively related to InfoTrade, while Order Imbalance and Illiquidity are negatively related. We do observe an increase in Abnormal Volume that is statistically significant, a fact that is consistent with the interpretation of excess volume in options prior to M&As of Augustin et al. (2015). In contrast, there is no significant abnormal signal behavior for the sample of earning announcements. This asymmetry is also present for option-based signals, reported in Panels C and D. The results are significant and similar to those of the unconditional sample in the case of M&As, while only two signals, IV Calls and Option

Illiquidity, are statistically negatively related to InfoTrade in the sample of earning announcements. Finally, Panels E and F report the results for mixed-market signals. Interestingly, we find that mixed-market signals display the same distinctive behavior in the presence of informed trading for both subsamples.

Overall, we find that mixed-market signals are more robust than single-market signals in detecting abnormal behavior when informed trading takes place, for both scheduled and unscheduled events. Generally, signals are more reliable in the case of informed trading around unscheduled events, that is, M&As. This finding could be seen as surprising, given that M&As are more difficult to time for regular traders. However, it could indicate that the presence of pseudo-informed investors acting around scheduled events can introduce additional noise, thus interfering with the signal extraction process.

Direction of Information. In our next test, we examine whether the quality of information signals relates to the sentiment of the information. More than 80% of all insider trades involve positive news, while slightly less than 20% involve negative news. We estimate the regression models for the two types of news for the model in (3). Table A5 of the Online Appendix reports the results for stock-based (Panels A and B), option-based (Panels C and D), and mixed-market signals (Panels E and F). A graphical summary of the results is displayed in Panel (d) of Figure 4.

Our findings indicate that stock-based signals show similar behavior, irrespective of the direction of information. The vivid exception is Realized Volatility, for which the signal becomes negative for the sample of negative news. In addition, statistical significance disappears for Lambda (for positive news) and for Illiquidity (for negative news). In contrast, option-based signals responses to informed trading are generally stronger for positive news. Most of the option-based signals (except for illiquidity) are statistically insignificant for negative news. The response of mixed-market signals is most robust across both types of trading direction.

6.2 Additional Evidence on the Use of Options

Choice of Option Contracts. In trading on private information using options, investors have the ability to choose options with different maturities and degrees of moneyness. An informed investor faces a variety of incentives that may favor one type of contract. From the perspective of a capital-constrained investor, more leveraged (OTM) contracts are attractive, since they provide higher gains for the same level of invested capital. From the perspective of feasibility, one would expect options with medium maturities to be most heavily used. Short-term maturities may not be useful unless the expiration date is after the information is publicly revealed. Long-term options are likely more expensive and less liquid and thus less attractive. We study the effect of these incentives by conditioning the aggregate Volume Ratio measures on both maturities and moneyness. Options with moneyness greater than 0.97 and less than 1.03 are defined as ATM. Any options with values outside of this range are classified as either in-the-money (ITM) or OTM. We further break down options into ultra-short (less than 10 days), short (10–30 days), medium (31–60 days), and long (>60 days) maturities. We estimate the regression models in (2) and (3) for the selected cross sections. The results are presented in Table A4 of the Online Appendix.

In Panel A of Table Table A4, we present the results from the baseline regression including firm and time fixed effects. Consistent with economic intuition, we find that the economic significance of the InfoTrade coefficient is highest for the short- and medium-term options and OTM options. Long-term options are by far the least significant predictor of informed trading. At the same time, even though ITM and ATM options are statistically significant predictors of informed trading, their economic significance is smaller. A similar effect can be observed for ultra-short options. In Panel B, we further adjust information measures by using the industry and size peers as benchmarks. The results are qualitatively identical and quantitatively close to those in Panel A. Overall, we conclude that option maturities and leverage are additional dimensions over which one can sharpen the predictions about informed trading.

Dynamics of Volume Ratios. One of the best-performing signals in our tests is Volume Ratio (VR). In this section, we ask two additional questions that shed more light on signal performance. First, we examine to what extent the predicting ability of information signals depends on the volume of the insiders themselves. As shown earlier, insider trading represents, on average, a meaningful fraction of the daily volume, especially in options. Thus, the abnormal behavior of VR could be a reflection of that fact. In Table A6 of the Online Appendix, we perform our baseline test but reestimate the VR measures by excluding the volume of insiders in either market. While the economic significance of the results decreases, the statistical relation remains intact. This result suggests that the variability of VR is unlikely to be solely due to insiders' trades. In market equilibrium, other market participants seem to react to the presence of informed traders. In this regard, the response of VR reflects both a direct effect due to insiders and an indirect effect due to other traders' responses to informed trading.

Second, we examine the behavior of VR around insider trading dates and public announcement dates. To this end, we plot the cross-sectional average of VR signals (for aggregate, call, put, and levered option volumes) for the window 35–21 days prior to insider trading; for the insider trading date, date 0; and for one to 15 days following the public announcement of the news on which insiders trade. Each signal is net of firm and time fixed effects to remove cross-sectional and time-series heterogeneity. We also include two standard errors bounds around the means. The results are presented in Figure 3. Consistent with our earlier results, we observe that each of the four measures spikes on date 0. In addition, we observe that the signals revert back to their normal levels following the public news release, a pattern consistent with informed trading taking place prior to the public news release.

7 Further Evidence on Illiquidity

One of the key findings in our study is the negative relation between informed trading events and stock/option Illiquidity and other liquidity measures. In this section, we explore this connection by analyzing the effect of trading horizons, company's size, and option listing.

Horizon Effects. One explanation of the negative relation between illiquidity and InfoTrade is based on strategic behavior of informed investors. In particular, if trading costs are high due to liquidity concerns, an informed investor may want to time the execution of their trades with regard to liquidity present in the market. To the extent that the market liquidity does not endogenously adjust to the entry of informed investors, one could observe low illiquidity levels when informed investors trade. This effect has been suggested by Collin-Dufresne and Fos (2015; 2016). The question remains whether such a pattern results from the strategic behavior of traders or is it driven by some other unobservable factor.

In this section, we want to shed more light on this issue by taking advantage of a specific feature of our data: the fact that we can observe the date when insiders *receive* a tip about firm fundamentals, the date when they use it, and the date when information is publicly revealed. In particular, we compare two scenarios: one (long information horizon) in which an insider has time to choose an optimal time of trade (from a liquidity perspective) and one (short information horizon) in which this possibility is constrained by public information disclosure. We define the latter scenario in our sample as one in which the number of days between the day the insider receives a tip and the time information is publicly disclosed is no greater than three days. Within such a short horizon, it would be hard to argue that an insider can time the decision to trade well.

To evaluate this hypothesis, we restrict our set of information signals to those that are more closely related to illiquidity: the bid–ask spread, Order Imbalance, Lambda, and Illiquidity. In Panel A of Table XIV, we show the results for the short information horizon sample. Although some of the previous negative relations for the spread disappear, which could be consistent with the idea of timing, the previously documented negative relation between illiquidity and InfoTrade remains unchanged. This result suggests that, when all firms are considered, the result is unlikely to be solely driven by the ability to time liquidity in the market.

Size Sorts. Insider traders in our sample execute trades in a large cross section of firms with different market capitalizations, trading costs, and liquidity costs. In this section, we examine to what extent the results in our paper depend on the firm market capitalization. Similar in spirit to the previous tests, we estimate our empirical model in (3) for the subsample of firms with market capitalization below and above the median value in the sample. The results, presented in Table A7 of the Online Appendix and summarized in Panel (a) of Figure 4, reveal two interesting facts. First, we do find that the behavior of illiquidity measures is strongly related to equity size. The negative relation with InfoTrade is particularly strong for the subset of companies with capitalization below the market median. The negative and statistically significant coefficient of Quoted Spread for small stocks suggests that informed traders use relatively more limit orders when trading these stocks.

Second, we find significant differences in the effect of InfoTrade on other type of information signals such as Price Range and Absolute Order Imbalance, which are only significant for small stocks, and Price Informativeness, which is only significant for large stocks. The spike in Abnormal Volume in options, in turn, is only significant for small stocks.

We further assess the robustness of this result in a subsample of investigations that are triggered by the Whistleblower Reward Program.The results presented in Table A8 of the Online Appendix demonstrate the robustness of the earlier findings. The negative illiquidity effect is mostly concentrated among companies that have small market capitalization. This is especially true for stock-based and mixed-market signals of illiquidity.

We also show the results for liquidity timing conditional on market capitalization in Panels B to E of Table XIV. Similarly, we show that the timing results are sensitive to firms' market capitalization. This is particularly true for the short-horizon subsample. For longer horizons, we observe that both small- and large-cap firms exhibit high liquidity episodes on days when insiders trade.

Overall, our results are consistent with the view that informed traders are more likely to strategically time trades on assets suffering from relatively high liquidity costs (that is, small caps). Informed traders are also more likely to trade such assets using limit orders. As such, the strong negative relation between private information use and illiquidity seems to be driven by small stocks.

Option Listings. Finally, we evaluate the illiquidity results through the lens of firms that have listed options. To the extent that such firms are generally more widely traded, one would expect that the stock-based signals for a subset of such companies would exhibit a weaker relation in terms of our illiquidity pattern. This is exactly what we find. In Table A9 of the Online Appendix, we show that the relation between stock-based illiquidity signals and InfoTrade becomes insignificant in the sample restricted to firms with listed options.

8 Concluding Remarks

Research to date has made several attempts to identify informed trading based on signals originating in publicly observed data, but this effort is empirically challenged by confounding effects and inherent measurement noise. We have attempted, in this paper, to exploit legal investigations to reconstruct precisely identified information flows and their associated trading plans to evaluate such signals against actual trades based on private information.

Our research sheds new light on how the traditional signals of informed trading perform and offers new insights for future investigations. From an empiricist point of view, we show that highly popular stock-based signals are relatively noisy and do not exhibit strong correlations with instances of real informed trading as predicted by theory. In turn, option-based signals, which are less studied in the literature, are desirable in this regard. Remarkably, some of the most robust signals are based on a mix of signals from both equity and derivative markets. Second, we show that the signal contained in volumes and in the ratio of the option volume to the the stock volume in particular is generally useful for predicting informed trading. Given that much of the empirical research to date has largely looked into bid–ask spread constructs and/or order flow imbalances as signals of information, this result calls for more emphasis on volume. This need seems to be increasingly important in more recent years, given the disruption of high-frequency trading (e.g., O'Hara, 2015). A structural PIN-like model that exploits volume, such as that of Back et al. (2016), and the volume-based imbalance measure of Easley et al. (2016) are promising steps in this direction.

The granularity of our data also allows us to provide novel evidence on the underlying mechanisms of information transmission and highlight the role of market capitalization, investor expertise, and the characteristics of the information event. Overall, our results suggest that perhaps more theoretical research is needed to understand the intricate interaction between informed trading and market learning by less informed market participants. They also highlight the importance of modeling information transmission considering a broader set of signals. A particularly interesting issue is the combination of signals that offers the best opportunity to learn about the presence of privately informed trading. We leave these exciting endeavors for future research.

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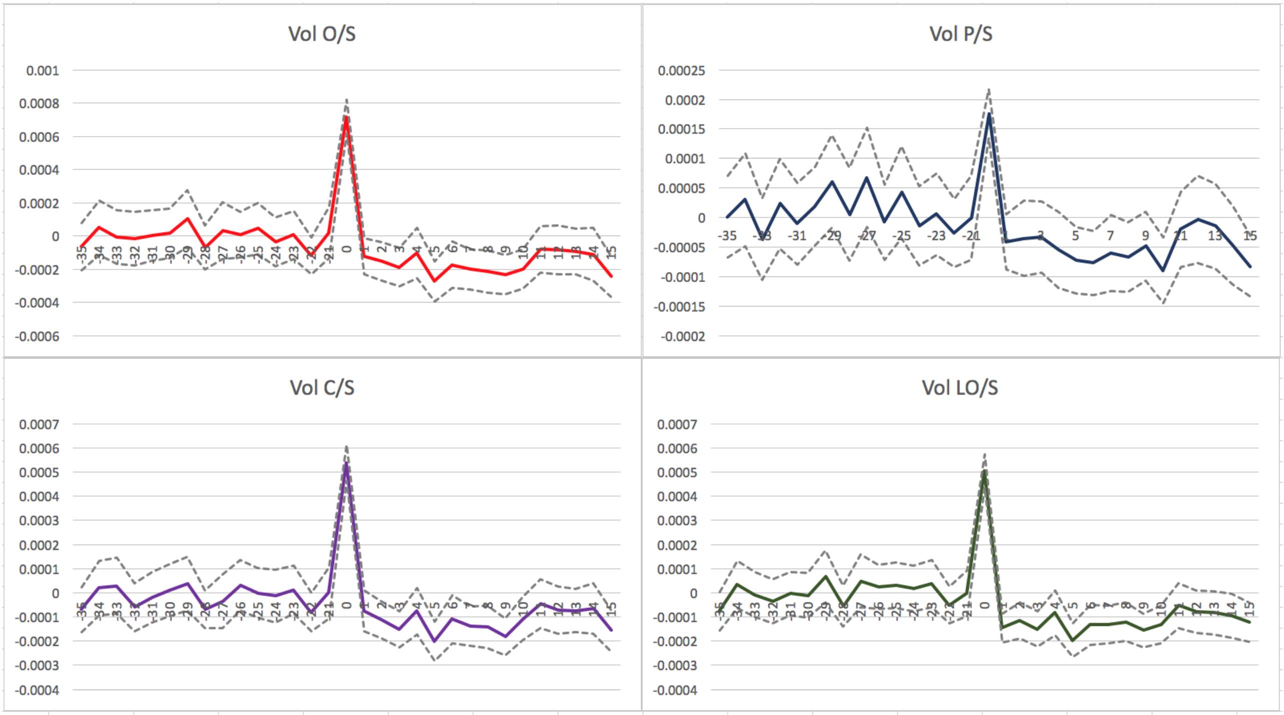
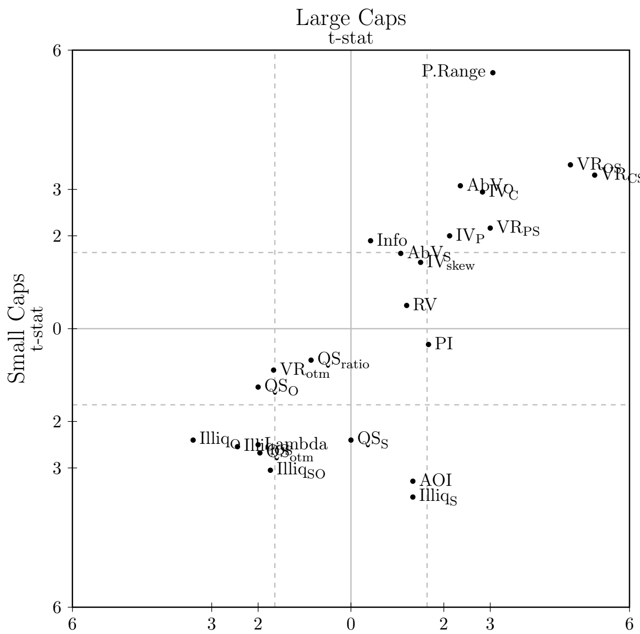
Figure 3. Option/Stock Volume Ratios

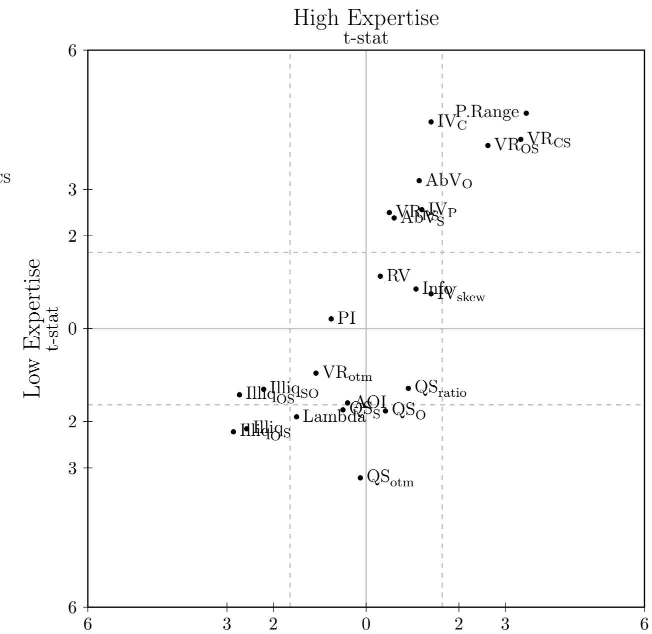


Note: The figure presents the average values (aggregated across all trades) of Volume Ratios, along with their two-standard-error bounds, around the event window of trading days for firms involved in insider trading. Time 0 indicates the date of insider trading. Times 1-15 denote time after the public announcement of the news. We exclude events in which insider trading happens within three trading days of the information (corporate) event. All measures are adjusted for firm and time fixed effects.

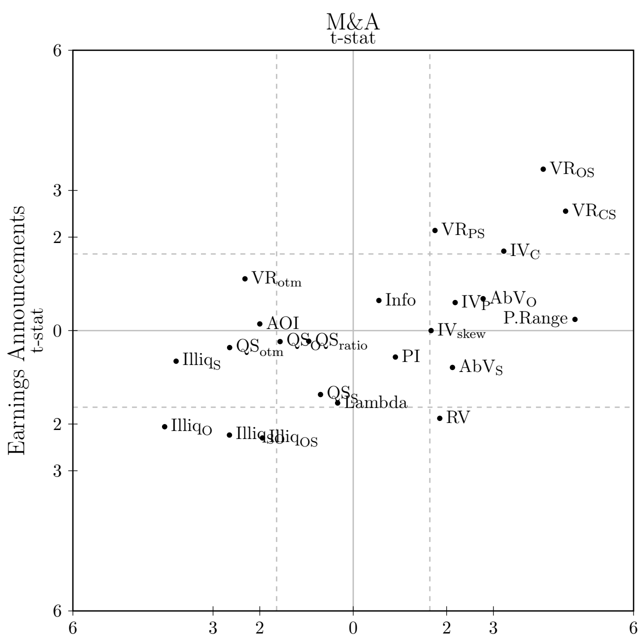
Figure 4. Cross-sectional Tests: Results Summary



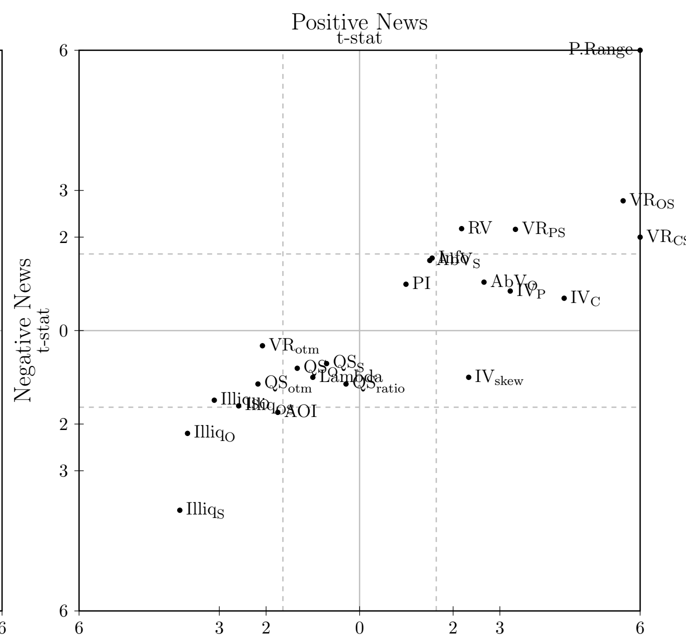
(a) Market Capitalization



(b) Trader Expertise



(c) Event Type



(d) News Direction

Table II
Information Signals and Controls: Descriptive Statistics

Panel A reports the mean, median, and standard deviation calculated across time and firms of stock-based information signals over the period 1995-2015. **Panel B** refers to option-based measures. **Panel C** refers to mixed stock-option-based measures. **Panel D** shows summary statistics for the control variables. The variable *LNSIZE* is the natural logarithm of the market value of equity, *LNVOL* is the natural logarithm of the stock trading volume, *TURNOVER* is stock turnover defined as the ratio of daily volume to the number of shares outstanding, and *PRC* is the stock price. The information signals in Panels A, B, and C are defined in Section 2. All information signals, *TURN*OVER, and *PRC* have been winsorized at the 1% level.

Variable	mean	median	st.dev.
Panel A: Stock-based signals			
Quoted spread *100	0.58	0.21	0.96
Price impact *100	10.82	4.71	17.57
Price range	4.86	3.68	3.99
Realized volatility (5 min; % per day)	0.25	0.01	0.89
Price informativeness	156.06	6.42	585.63
Absolute order imbalance	0.15	0.11	0.17
Abnormal volume	43.58	-12.95	2983.23
Lambda	0.16	0.03	0.34
Illiquidity	0.60	0.04	2.98
Panel B: Option-based signals			
Quoted spread (all options)	0.58	0.48	0.37
Quoted spread (otm options)	0.84	0.75	0.48
Implied volatility Calls	0.55	0.48	0.26
Implied volatility Puts	0.59	0.51	0.27
Implied volatility skew	-0.01	-0.01	0.05
Abnormal volume	274.76	-33.15	9736.33
Volume ratio (otm/all options)	29.28	2.28	43.45
Illiquidity *100	0.15	0.004	0.66
Panel C: Mixed signals			
Quoted spread ratio (O/S)	674.23	390.50	853.90
Volume ratio all options/stock *100	0.13	0.05	0.22
Volume ratio calls/stock *100	0.09	0.03	0.15
Volume ratio puts/stock *100	0.05	0.01	0.10
Illiquidity S/O*1,000	0.47	0.03	1.85
Illiquidity O/S *1,000,000	0.21	0.03	0.69
Panel D: Control variables			
LNSIZE	13.49	13.39	1.97
LNVOL	12.74	12.92	2.31
TURNOVER	1.25%	0.82%	1.31%
PRC	23.05	16.83	21.27

Table III
Trade Characteristics: Descriptive Statistics

The unit of observation is the insider trade. **Panel A** classifies trades by trading instrument. **Panel B** classifies trades by the direction of trading. **Panel C** shows the distribution of trades by year. **Panel D** shows the distribution of insider trades with respect to the traded company's primary two-digit SIC code. **Panel E** reports various trading statistics.

Panel A: Distribution of Trading Instruments	**Number of trades**	**Percentage of trades**
Stocks	3,392	67.06
Options	1,610	31.83
ADS	44	0.87
Bonds	12	0.33
Total	5,058	100
Panel B: Distribution of Buys and Sells		
Buys	4,220	83.43
Sales	838	16.57
Panel C: Distribution of Trades by Year		
1995	17	0.34
1996	1	0.02
1997	14	0.28
1998	57	1.13
1999	100	1.98
2000	238	4.71
2001	167	3.3
2002	206	4.07
2003	205	4.05
2004	208	4.11
2005	247	4.88
2006	394	7.79
2007	795	15.72
2008	633	12.51
2009	504	9.96
2010	375	7.41
2011	355	7.02
2012	284	5.61
2013	133	2.63
2014	111	2.19
2015	14	0.28

Table III (Continued)

Trade Characteristics: Descriptive Statistics

Panel D: Distribution of trades by SIC2 Industry Code

	SIC2 Code	**Number of Trades**	**Percent of trades**
Chemicals	28	752	16.09
Business Services	73	673	14.40
Electronic Equipment	36	494	10.57
Measuring and Controlling Equipment	38	318	6.80
Industrial and Commercial Machinery	35	220	4.71
Depositary Institutions	60	192	4.11
Wholesale Trade: Durable Goods	50	138	2.95
Engineering and Management Services	87	132	2.82
Wholesale Trade: Nondurable Goods	51	127	2.72
Oil and Gas Extraction	13	103	2.20

Panel E: Trading Statistics

Characteristic	mean	median	st. dev.	min	max
Distance from news to trade	8.05	2	23.88	0	417
Distance from trade to event	24.77	7	61.59	0	998
Distance from first to last trade	19.23	8	73.34	1	738
Firms per case	4.72	2	5.32	1	25
Traders per case	5.06	3	4.55	1	18
Trades per firm	31.47	16	45.17	1	231
Trades per trader	20.26	10	24.05	1	97
Trader age	47.38	46	11.75	22	82
Tipper age	46.26	45	11.64	25	80
Trader gender (male in %)	91.67	-	-	-	-
Tipper gender (male in %)	92.73	-	-	-	-
Trader finance background (in %)	60.06	-	-	-	-
Trader top executive (in %)	29.97	-	-	-	-
Reported profit ($1,000s)	1013.6	90.00	7926.8	4.0	27500

Table IV
Measuring the Information Content of Trades

The return is based on stock price data and is computed from the open price on the insider trading day to the open price on the day following the public disclosure date. The returns are split according to positive and negative news. The aggregate return considers the absolute value of each return. The returns for 13D filers are measured from the open price of the day 13D filers trade to the open price of the day following the public disclosure date of the trade. ***, **, * denote 1%, 5%, and 10% level of statistical significance, respectively.

	Positive	Negative	Aggregate	
	Illegal Insider Trading			13D Filers
Mean Return (%)	43.510***	-18.564***	38.271***	4.927***
	(4.199)	(2.142)	(3.389)	(0.638)
Median Return (%)	33.690***	-15.322***	29.427***	2.401***
	(2.348)	(2.545)	(2.275)	(0.173)
#Obs	2,351	696	3,055	2,628

Table V
Relative Importance of Insider Trades: Summary Statistics

Security	Stocks	Calls	Puts
Mean (%)	10.2	38.1	31.5
Median (%)	2.8	23.3	13.9
Standard deviation (%)	22.2	39.9	38.5

Table VI
Stock-based Signals: Baseline Test Specification

The dependent variables are daily stock-based signals measured at the company level over the period 1995-2015. InfoTrade is an indicator variable equal to one for days of insider trading activity and zero for the trading window 35–21 days prior to the first insider trading date in each firm. We exclude all trades that occur within three trading days prior to the public information release. All definitions of control variables, measured at the daily frequency, mirror those in Table II. **Panel A** considers a baseline specification. **Panel B** additionally includes firm and time fixed effects. **Panel C** additionally adjusts information signals, subtracting the average value of the portfolio of matched firms. The matching is performed along two-digit SIC industry codes and the same market capitalization quintile. Standard errors (in parentheses) are clustered around firms. ***, **, * denote 1%, 5%, and 10% level of statistical significance, respectively.

Based on			Prices				Volume		Both
	Quoted Spread	Price Impact	Price Range	Realized Volatility	Price Inform.	Order Imb.	Abn. Volume	Lambda	Illiq.
Panel A: Baseline estimates									
InfoTrade	-0.113***	-1.034**	0.530***	0.009	30.77*	-0.018***	291.20*	-0.036***	-0.348***
	(0.028)	(0.437)	(0.149)	(0.031)	(18.406)	(0.005)	(149.08)	(0.009)	(0.083)
LNSIZE	-0.179**	-3.007***	-1.019***	-0.151***	-57.78***	-0.013*	-47.609	-0.124***	0.165
	(0.060)	(0.582)	(0.210)	(0.043)	(8.657)	(0.007)	(63.899)	(0.014)	(0.132)
LNVOL	-0.092*	-0.725	0.572***	0.036	13.780*	-0.021***	-5.438	0.042***	-0.643***
	(0.056)	(0.498)	(0.117)	(0.034)	(7.496)	(0.007)	(10.439)	(0.010)	(0.139)
TURNOVER	-2.184	-134.8***	16.683	-1.582	-558.79	0.120	14,305***	-7.744***	30.297***
	(4.714)	(50.255)	(13.707)	(3.666)	(896.49)	(0.585)	(5,198)	(1.291)	(10.853)
PRC	-0.002	-0.034	-0.010	0.001	0.569	-0.000	0.024	0.001	-0.007
	(0.003)	(0.028)	(0.013)	(0.002)	(0.531)	(0.000)	(4.369)	(0.001)	(0.006)
Constant	0.564***	10.62***	4.774***	0.262***	158.859***	0.155***	-35.446	0.165***	0.598***
	(0.030)	(0.397)	(0.125)	(0.027)	(7.336)	(0.004)	(32.853)	(0.011)	(0.068)
#Obs	12,146	12,096	12,277	11,319	10,175	12,123	12,252	12,081	12,202
Panel B: With time and firm fixed effects									
InfoTrade	-0.057***	-0.026	0.802***	0.043*	42.54**	-0.012***	321.9**	-0.015*	-0.288***
	(0.021)	(0.377)	(0.128)	(0.023)	(18.98)	(0.004)	(151.2)	(0.008)	(0.082)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	12,146	12,096	12,277	11,319	10,175	12,123	12,252	12,081	12,202
Panel C: With time and firm fixed effects (control group adjusted)									
InfoTrade	-0.039**	0.055	0.787***	0.017	32.48*	-0.008**	169.65	-0.015**	-0.286***
	(0.016)	(0.341)	(0.123)	(0.019)	(18.40)	(0.003)	(106.57)	(0.006)	(0.082)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	12,146	12,096	12,277	11,319	10,175	12,123	12,252	12,081	12,202

Table VII
Option-based Signals: Baseline Test Specification

The dependent variables are daily option-based signals measured at the company level over the period 1995-2015. The variable InfoTrade is an indicator variable equal to one for days of insider trading activity and zero for the trading window 35–21 days prior to the first insider trading date in each firm. We exclude all trades that occur within three trading days prior to public information release. All definitions of control variables, measured at the daily frequency, mirror those in Table II. **Panel A** considers a baseline specification. **Panel B** additionally includes firm and time fixed effects. **Panel C** additionally adjust the information signals, subtracting the average value of the portfolio of matched firms. The matching is performed along two-digit SIC industry codes and the same market capitalization quintile. Standard errors (in parentheses) are clustered around firms. ***, **, * denote 1%, 5%, and 10% level of statistical significance, respectively.

Based on	Prices					Volume		Both
	Quoted Spread (all)	Quoted Spread (otm)	IV Calls	IV Puts	IV Skew	Abn. Volume	Volume Ratio (otm/all)	Illiq.
Panel A: Baseline estimates								
InfoTrade	-0.018	-0.041*	0.013	0.007	0.004*	1,549.8***	-4.810**	-0.125***
	(0.020)	(0.025)	(0.012)	(0.013)	(0.002)	(477.4)	(1.879)	(0.024)
LNSIZE	-0.063**	-0.055	-0.137***	-0.127**	-0.003	-240.01	-7.968***	0.062*
	(0.029)	(0.035)	(0.047)	(0.053)	(0.003)	(279.201)	(2.100)	(0.036)
LNVOL	-0.023	-0.058	0.108***	0.099**	0.003	-84.368	-1.436	-0.146***
	(0.030)	(0.036)	(0.036)	(0.041)	(0.003)	(166.916)	(2.177)	(0.041)
TURNOVER	-3.966*	-2.228	-3.078	-1.906	-0.562*	38,510.8*	-697.9***	2.364
	(2.241)	(2.610)	(2.835)	(3.249)	(0.308)	(22,296.6)	(167.977)	(2.339)
PRC	-0.002*	-0.003**	-0.000	0.000	-0.000	5.415	-0.079	-0.003***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.000)	(14.737)	(0.082)	(0.001)
Constant	0.643***	0.929***	0.570***	0.611***	-0.011***	-164.1*	37.07***	0.252***
	(0.019)	(0.023)	(0.015)	(0.017)	(0.002)	(88.57)	(1.410)	(0.026)
#Obs	8,372	8,372	8,253	8,114	7,996	8,454	8,464	7,548
Panel B: With time and firm fixed effects								
InfoTrade	-0.020	-0.048**	0.028***	0.020***	0.005	1,624.1***	-3.181*	-0.107***
	(0.017)	(0.023)	(0.007)	(0.007)	(0.003)	(458.5)	(1.694)	(0.021)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	8,372	8,372	8,253	8,114	7,996	8,454	8,464	7,548
Panel C: With time and firm fixed effects (control group adjusted)								
InfoTrade	-0.025	-0.050**	0.030***	0.024***	0.005*	1,151.2***	-3.310**	-0.083***
	(0.016)	(0.022)	(0.007)	(0.007)	(0.003)	(406.1)	(1.609)	(0.020)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	8,372	8,372	8,253	8,114	7,996	8,454	8,464	7,548

Table VIII
Mixed-Market Signals: Baseline Test Specification

The dependent variables are daily stock- and option-based (mixed) signals measured at the company level over the period 1995-2015. InfoTrade is an indicator variable equal to one for days of insider trading activity and zero for the trading window 35–21 days prior to the first insider trading date in each firm. We exclude all trades that occur within three trading days prior to public information release. All definitions of control variables, measured at the daily frequency, mirror those in Table II. **Panel A** considers a baseline specification. **Panel B** additionally includes firm and time fixed effects. **Panel C** additionally adjust the information signals, subtracting the average value of the portfolio of matched firms. The matching is performed along two-digit SIC industry codes and the same market capitalization quintile. Standard errors (in parentheses) are clustered around firms. ***, **, * denote 1%, 5%, and 10% level of statistical significance, respectively.

Based on	Prices	Volume			Both	
	Quoted Spread Ratio	Volume Ratio O/S	Volume Ratio Calls/S	Volume Ratio Puts/S	Illiq. S/O	Illiq. O/S
Panel A: Baseline estimates						
InfoTrade	32.569	0.057***	0.046***	0.009***	-0.298***	-0.100***
	(41.274)	(0.010)	(0.008)	(0.003)	(0.060)	(0.023)
LNSIZE	289.0***	-0.015	-0.009	-0.006	-0.093	0.063
	(59.109)	(0.012)	(0.007)	(0.006)	(0.092)	(0.055)
LNVOL	-339.65***	0.020*	0.011	0.009*	-0.157	-0.201***
	(66.609)	(0.012)	(0.007)	(0.005)	(0.101)	(0.061)
TURNOVER	19,430.35***	-0.295	-0.165	-0.090	-7.979	4.581
	(4,421.167)	(1.054)	(0.654)	(0.485)	(6.234)	(3.504)
PRC	1.005	0.003***	0.002***	0.001***	-0.003	-0.004**
	(2.928)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)
Constant	672.90***	0.101***	0.063***	0.037***	0.766***	0.332***
	(39.722)	(0.007)	(0.004)	(0.003)	(0.060)	(0.035)
#Obs	8,123	8,464	8,463	8,464	7,648	8,221
Panel B: With time and firm fixed effects						
InfoTrade	-19.212	0.057***	0.045***	0.011***	-0.217***	-0.076***
	(31.859)	(0.009)	(0.007)	(0.003)	(0.055)	(0.024)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	8,123	8,464	8,463	8,464	7,648	8,221
Panel C: With time and firm fixed effects (control group adjusted)						
InfoTrade	-26.398	0.054***	0.041***	0.011***	-0.177***	-0.067***
	(29.546)	(0.009)	(0.007)	(0.003)	(0.053)	(0.023)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	8,123	8,464	8,463	8,464	7,648	8,221

Table IX
Conditioning on Trade Intensity

The dependent variables are information signals. This table presents different results for trade of trades of low and high intensity. **Panels A and B** report the results for stock-based signals, **Panels C and D** the results for option-based signals, and **Panels E and F** the results for mixed signals. The variable InfoTrade is an indicator variable equal to one for days of insider trading activity and zero for trading window 35-21 days prior to the first insider trading date in each firm. We exclude all trades that occur within three trading days prior to public information release. All definitions of the control variables, measured at the daily frequency, mirror those in Table II. All panels include firm and time fixed effects and additionally adjust the information signals, subtracting average values of the portfolio of matched firms. The matching is performed along two-digit SIC industry codes and the same market capitalization quintile. Standard errors (in parentheses) are clustered around firms. ***, **, * denote 1%, 5%, and 10% level of statistical significance, respectively.

Based on	**Prices**					**Volume**		**Both**	
	Quoted Spread	Price Impact	Price Range	Realized Volatility	Price Inform.	Order Imb.	Abn. Volume	Lambda	Illiq.
Panel A: Stock-based Signals: Low Intensity									
InfoTrade	-0.013	-0.118	0.729***	-0.005	17.082	0.003	97.291	-0.013	-0.046
	(0.012)	(0.330)	(0.175)	(0.024)	(29.946)	(0.004)	(216.796)	(0.008)	(0.044)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	4,761	4,761	4,761	4,680	4,407	4,761	4,758	4,761	4,761
Panel B: Stock-based Signals: High Intensity									
InfoTrade	-0.065	-0.039	1.070***	0.037	52.066	-0.024***	81.446	-0.020	-0.784***
	(0.044)	(0.820)	(0.218)	(0.043)	(33.745)	(0.007)	(96.733)	(0.012)	(0.231)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	4,522	4,484	4,546	3,890	3,292	4,484	4,524	4,470	4,495

	Quoted Spread (all)	Quoted Spread (otm)	IV Calls	IV Puts	IV Skew	Abn. Volume	Volume Ratio (otm/all)	Illiq.
Panel C: Option-based Signals: Low Intensity								
InfoTrade	-0.025	-0.077**	0.016	0.020	0.004	2,684.200*	-5.065	-0.060***
	(0.026)	(0.038)	(0.012)	(0.022)	(0.004)	(1,428.692)	(3.642)	(0.020)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	1,485	1,485	1,516	1,511	1,472	1,522	1,522	1,468
Panel D: Option-based Signals: High Intensity								
InfoTrade	-0.048	-0.056	0.023**	0.013	0.004	782.341**	-3.580	-0.129***
	(0.029)	(0.039)	(0.010)	(0.009)	(0.003)	(377.021)	(3.099)	(0.046)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	1,909	1,909	1,943	1,922	1,707	1,943	1,943	1,797

Table IX
Conditioning on Trade Intensity

Based on	**Prices**		**Volume**		**Both**	
	Quoted Spread Ratio	Volume Ratio O/S	Volume Ratio Calls/S	Volume Ratio Puts/S	Illiq. S/O	Illiq. O/S
Panel E: Mixed-market Signals: Low Intensity						
InfoTrade	-58.370	0.085***	0.059***	0.023**	-0.157***	-0.016
	(59.786)	(0.030)	(0.020)	(0.010)	(0.049)	(0.014)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	1,458	1,522	1,522	1,522	1,479	1,510
Panel F: Mixed-market Signals: High Intensity						
InfoTrade	-24.396	0.098***	0.082***	0.013**	-0.342**	-0.030
	(81.012)	(0.022)	(0.018)	(0.005)	(0.130)	(0.054)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	1,826	1,943	1,943	1,943	1,800	1,940

Table X
SEC Whistleblower Cases: Summary Statistics

Characteristic/Sample	WB=1	WB=0
Number of Cases	37	129
Distance from news to trade	12.23	12.19
Distance from trade to event	24.28	21.37
Distance from first to last trade	24.13	17.73
Trades per firm	18.28	14.20
Trades per trader	25.94	25.64
Market capitalization (in Billions)	13.90	3.58
Reported profits (in Millions)	1.49	1.22

Table XI
Conditioning on SEC Whistleblower Cases

This table presents results for the subsample of whistleblower cases. The dependent variables are information signals. **Panel A** reports results for stock-based signals, **Panel B** the results for option-based signals, and **Panel C** the results for mixed signals. The variable InfoTrade is an indicator variable equal to one for days of insider trading activity and zero for trading window 35-21 days prior to the first insider trading date in each firm. We exclude all trades that occur within three trading days prior to public information release. All definitions of the control variables, measured at the daily frequency, mirror those in Table II. All panels include firm and time fixed effects and additionally adjust the information signals, subtracting average values of the portfolio of matched firms. The matching is performed along two-digit SIC industry codes and the same market capitalization quintile. Standard errors (in parentheses) are clustered around firms. ***, **, * denote 1%, 5%, and 10% level of statistical significance, respectively.

Based on	**Prices**					**Volume**		**Both**	
	Quoted Spread	Price Impact	Price Range	Realized Volatility	Price Inform.	Order Imb.	Abn. Volume	Lambda	Illiq.
Panel A: Stock-based Signals									
InfoTrade	-0.032**	-0.068	0.729***	0.025	-8.381	-0.013***	237.384*	-0.032***	-0.166**
	(0.015)	(0.531)	(0.179)	(0.020)	(22.328)	(0.005)	(125.892)	(0.009)	(0.072)
WB	0.044	0.489	-0.419	0.005	-161.559***	0.036	-991.699	-0.014	0.065
	(0.061)	(1.183)	(0.470)	(0.019)	(38.925)	(0.024)	(1,008.543)	(0.013)	(0.071)
InfoTrade*WB	0.034	0.528	0.136	-0.007	52.542	0.013	-140.264	0.032**	0.166**
	(0.024)	(0.917)	(0.340)	(0.037)	(53.372)	(0.008)	(414.305)	(0.016)	(0.077)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	6,407	6,405	6,449	6,368	6,054	6,405	6,448	6,405	6,433
	Quoted Spread (all)	Quoted Spread (otm)	IV Calls	IV Puts	IV Skew	Abn. Volume	Volume Ratio (otm/all)	Illiq.	
Panel B: Option-based Signals									
InfoTrade	-0.062**	-0.105***	0.045***	0.044***	0.008	1,123.449**	-4.021	-0.112***	
	(0.029)	(0.038)	(0.011)	(0.011)	(0.006)	(475.622)	(2.605)	(0.036)	
WB	-0.030	-0.110*	0.006	0.020	-0.006	2,905.753	12.034	0.051	
	(0.050)	(0.058)	(0.042)	(0.044)	(0.004)	(2,733.283)	(9.911)	(0.051)	
InfoTrade*WB	0.048	0.092	-0.022	-0.025	-0.005	-881.373	-0.039	0.028	
	(0.045)	(0.059)	(0.022)	(0.029)	(0.008)	(1,001.494)	(4.552)	(0.052)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
#Obs	4,761	4,761	4,669	4,565	4,385	4,850	4,853	4,267	

Table XI
Conditioning on SEC Whistleblower Cases

Based on	Prices	Volume			Both	
Panel C: Mixed-market Signals						
	Quoted Spread Ratio	Volume Ratio O/S	Volume Ratio Calls/S	Volume Ratio Puts/S	Illiq. S/O	Illiq. O/S
InfoTrade	-63.027	0.064***	0.044***	0.020***	-0.209**	-0.121***
	(59.964)	(0.014)	(0.010)	(0.005)	(0.097)	(0.037)
WB	157.243*	0.074*	0.039	0.034**	0.259	-0.017
	(92.804)	(0.039)	(0.024)	(0.016)	(0.221)	(0.032)
InfoTrade*WB	83.364	-0.047	-0.023	-0.024**	0.052	0.031
	(84.446)	(0.032)	(0.022)	(0.011)	(0.136)	(0.061)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	4,696	4,853	4,852	4,853	4,338	4,647

Table XII
Signal Behavior on Information Transmission Date

The dependent variables are information signals. **Panel A** reports the results for stock-based signals, **Panel B** the results for option-based signals, and **Panel C** the results for mixed signals. The variable *InfoRec* is an indicator variable equal to one for days when the trader receives private information, rather than when she trades based on it, and zero for trading window 35–21 days prior to that day. We exclude all trades that occur within three trading days prior to public information release. All definitions of the control variables, measured at the daily frequency, mirror those in Table II. All panels include firm and time fixed effects and additionally adjust the information signals, subtracting average values of the portfolio of matched firms. The matching is performed along two-digit SIC industry codes and the same market capitalization quintile. Standard errors (in parentheses) are clustered around firms. ***, **, * denote 1%, 5%, and 10% level of statistical significance, respectively.

Panel A: Stock-based Signals

	Quoted Spread	Price Impact	Price Range	Realized Volatility	Price Inform.	Order Imb.	Abn. Volume	Lambda	Illiq.
InfoRec	-0.047*	-0.193	0.070	-0.030	18.024	0.001	-53.755	0.000	-0.198*
	(0.022)	(0.692)	(0.152)	(0.023)	(28.618)	(0.007)	(185.324)	(0.009)	(0.109)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	3,177	3,166	3,185	3,028	2,807	3,166	3,178	3,162	3,170

Panel B: Option-based Signals

	Quoted Spread (all)	Quoted Spread (otm)	IV Calls	IV Puts	IV Skew	Abn. Volume	Volume Ratio (otm/all)	Illiq.
InfoRec	0.000	-0.021	0.015*	0.013	0.003	281.393	-1.266	-0.098***
	(0.022)	(0.029)	(0.008)	(0.010)	(0.003)	(762.889)	(2.689)	(0.035)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	3,806	3,806	3,781	3,728	3,716	3,818	3,823	3,429

Panel C: Mixed-market Signals

	Quoted Spread Ratio	Volume Ratio O/S	Volume Ratio Calls/S	Volume Ratio Puts/S	Illiq. S/O	Illiq. O/S
InfoRec	-61.635	0.009	0.008	0.001	-0.138	0.003
	(42.486)	(0.015)	(0.009)	(0.008)	(0.105)	(0.044)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	2,246	2,311	2,311	2,311	2,105	2,297

Table XIII
Conditioning on Trader Expertise

This table presents separate results for traders executed by traders with low or high trading expertise. The dependent variables are information signals. **Panels A and B** report the results for stock-based signals, **Panels C and D** the results for option-based signals, and **Panels E and F** the results for mixed signals. The variable InfoTrade is an indicator variable equal to one for days of insider trading activity and zero for trading window 35-21 days prior to the first insider trading date in each firm. We exclude all trades that occur within three trading days prior to public information release. All definitions of the control variables, measured at the daily frequency, mirror those in Table II. All panels include firm and time fixed effects and additionally adjust the information signals, subtracting average values of the portfolio of matched firms. The matching is performed along two-digit SIC industry codes and the same market capitalization quintile. Standard errors (in parentheses) are clustered around firms. ***, **, * denote 1%, 5%, and 10% level of statistical significance, respectively.

Based on			**Prices**			**Volume**		**Both**	
	Quoted Spread	Price Impact	Price Range	Realized Volatility	Price Inform.	Order Imb.	Abn. Volume	Lambda	Illiq.
			Panel A: Stock-based Signals: Low Expertise						
InfoTrade	-0.035*	0.112	0.854***	0.026	24.720	-0.008	279.748**	-0.019*	-0.287**
	(0.020)	(0.532)	(0.184)	(0.023)	(28.924)	(0.005)	(117.297)	(0.010)	(0.133)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	4,948	4,931	5,041	4,676	4,324	4,931	5,022	4,920	5,001
			Panel B: Stock-based Signals: High Expertise						
InfoTrade	-0.009	-0.413	0.711***	0.011	33.606	-0.002	139.508	-0.015	-0.201**
	(0.018)	(0.548)	(0.206)	(0.036)	(31.277)	(0.005)	(231.065)	(0.010)	(0.078)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	5,125	5,110	5,148	4,815	4,215	5,110	5,142	5,107	5,132
	Quoted Spread (all)	Quoted Spread (otm)	IV Calls	IV Puts	IV Skew	Abn. Volume	Volume Ratio (otm/all)	Illiq.	
			Panel C: Option-based Signals: Low Expertise						
InfoTrade	-0.039*	-0.090***	0.049***	0.041**	0.003	1,153.204***	-2.147	-0.080**	
	(0.022)	(0.028)	(0.011)	(0.016)	(0.004)	(361.757)	(2.241)	(0.036)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
#Obs	3,343	3,343	3,286	3,222	3,189	3,395	3,399	3,007	
			Panel D: Option-based Signals: High Expertise						
InfoTrade	0.010	-0.005	0.014	0.012	0.007	940.118	-3.069	-0.103***	
	(0.024)	(0.040)	(0.010)	(0.010)	(0.005)	(821.802)	(2.837)	(0.036)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
#Obs	3,506	3,506	3,500	3,456	3,332	3,535	3,541	3,237	

Table XIII
Conditioning on Trader Expertise

Based on	**Prices**	**Volume**			**Both**	
	Quoted Spread Ratio	Volume Ratio O/S	Volume Ratio Calls/S	Volume Ratio Puts/S	Illiq. S/O	Illiq. O/S
Panel E: Mixed-market Signals: Low Expertise						
InfoTrade	-58.486	0.071***	0.053***	0.015**	-0.124	-0.057
	(45.493)	(0.018)	(0.013)	(0.006)	(0.095)	(0.040)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	3,252	3,399	3,398	3,399	3,062	3,272
Panel F: Mixed-market Signals: High Expertise						
InfoTrade	48.042	0.021***	0.020***	0.002	-0.201**	-0.071***
	(52.800)	(0.008)	(0.006)	(0.004)	(0.091)	(0.026)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	3,379	3,541	3,541	3,541	3,263	3,493

Table XIV
Tests on Strategic Timing

This table presents separate results for long and short information horizons. A long (short) horizon is defined as one containing more than (less than or exactly) three trading days between the time in which information is received by the trader and the date of its public disclosure. The dependent variables are information signals. **Panel A** reports the results for short horizons and all assets, **Panels B and C** the results for long horizons and large and small caps, respectively, and **Panels D and E** the results for short horizons and large and small caps, respectively. The variable InfoTrade is an indicator variable equal to one for days of insider trading activity and zero for trading window 35-21 days prior to the first insider trading date in each firm. We exclude all trades that occur within three trading days prior to public information release. All definitions of the control variables, measured at the daily frequency, mirror those in Table II. All panels include firm and time fixed effects and additionally adjust the information signals, subtracting average values of the portfolio of matched firms. The matching is performed along two-digit SIC industry codes and the same market capitalization quintile. Standard errors (in parentheses) are clustered around firms. ***, **, * denote 1%, 5%, and 10% level of statistical significance, respectively.

Market	**Stock**				**Option**	
	Quoted Spread	Order Imbalance	Lambda	Illiq.	Quoted Spread otm	Illiq.
Panel A: Short information horizon - All Market Caps						
InfoTrade	0.073	-0.000	-0.026	-0.417**	0.063	-0.131*
	(0.081)	(0.018)	(0.028)	(0.159)	(0.066)	(0.077)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	731	728	725	729	428	393
Panel B: Long information horizon - Large Caps						
InfoTrade	0.002	0.000	-0.002	0.007	-0.064	-0.071***
	(0.006)	(0.004)	(0.001)	(0.014)	(0.043)	(0.026)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	2,821	2,821	2,821	2,836	2,535	2,457
Panel C: Long information horizon - Small Caps						
InfoTrade	-0.108**	-0.023**	-0.035**	-0.637***	-0.099**	-0.190**
	(0.053)	(0.009)	(0.015)	(0.224)	(0.047)	(0.076)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	3,065	3,047	3,041	3,072	1,520	1,166
Panel D: Short information horizon - Large Caps						
InfoTrade	0.057	0.025*	-0.006*	-0.134**	-0.003	-0.017
	(0.069)	(0.015)	(0.004)	(0.058)	(0.069)	(0.045)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	373	373	373	373	318	300
Panel E: Short information horizon - Small Caps						
InfoTrade	0.089	-0.026	-0.046	-0.720**	0.250	-0.418*
	(0.151)	(0.032)	(0.058)	(0.308)	(0.143)	(0.196)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	358	355	352	356	110	93

Appendix A Online Appendix to “Chasing Private Information”

Table A1
Conditioning on Complexity

This table presents the results conditioning on the number of firms in the investigation. The dependent variables are information signals. **Panel A** reports the results for stock-based signals, **Panel B** the results for option-based signals, and **Panel C** the results for mixed signals. The variable InfoTrade is an indicator variable equal to one for days of insider trading activity and zero for trading window 35-21 days prior to the first insider trading date in each firm. We exclude all trades that occur within three trading days prior to public information release. All definitions of the control variables, measured at the daily frequency, mirror those in Table II. All panels include firm and time fixed effects and additionally adjust the information signals, subtracting average values of the portfolio of matched firms. The matching is performed along two-digit SIC industry codes and the same market capitalization quintile. Standard errors (in parentheses) are clustered around firms. ***, **, * denote 1%, 5%, and 10% level of statistical significance, respectively.

Based on	**Prices**					**Volume**		**Both**	
Panel A: Stock-based signals									
	Quoted Spread	Price Impact	Price Range	Realized Volatility	Price Inform.	Order Imb.	Abn. Volume	Lambda	Daily Illiq.
InfoTrade	-0.055***	-0.268	0.933***	0.025	25.720	-0.010**	174.821	-0.031***	-0.166**
	(0.017)	(0.471)	(0.165)	(0.021)	(27.234)	(0.005)	(127.980)	(0.008)	(0.073)
Firms	0.084	1.423	-0.590	0.056	152.824**	-0.000	-275.900	0.033	0.116
	(0.056)	(1.141)	(0.384)	(0.057)	(70.263)	(0.019)	(632.000)	(0.021)	(0.143)
InfoTrade*Firms	0.029	0.588	-0.268	-0.014	12.061	0.003	-9.046	0.031***	-0.223
	(0.032)	(0.676)	(0.236)	(0.037)	(37.315)	(0.007)	(208.375)	(0.011)	(0.157)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	12,146	12,096	12,277	11,319	10,175	12,123	12,252	12,081	12,202
	Quoted Spread (all)	Quoted Spread (otm)	IV Calls	IV Puts	IV Skew	Abn. Volume	Volume Ratio (otm/all)	Illiq.	
Panel B: Option-based signals									
InfoTrade	-0.038	-0.064*	0.030***	0.032**	0.004	394.770	-3.832	-0.116***	
	(0.025)	(0.034)	(0.009)	(0.013)	(0.003)	(439.967)	(2.648)	(0.034)	
Firms	0.034	0.046	-0.048	-0.044	0.005	-3,312.331	-1.274	-0.057**	
	(0.081)	(0.128)	(0.063)	(0.047)	(0.008)	(2,608.370)	(5.376)	(0.025)	
InfoTrade*Firms	0.023	0.026	0.000	-0.016	0.001	1,408.409*	0.970	0.063	
	(0.032)	(0.043)	(0.014)	(0.016)	(0.005)	(777.188)	(3.195)	(0.041)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
#Obs	8,372	8,372	8,253	8,114	7,996	8,454	8,464	7,548	

Table A1

Conditioning on Complexity

Based on	**Prices**	**Volume**			**Both**	
Panel C: Mixed Market Signals						
	Quoted Spread Ratio	Volume Ratio O/S	Volume Ratio Calls/S	Volume Ratio Puts/S	Illiq. S/O	Illiq. O/S
InfoTrade	-62.444	0.047***	0.037***	0.009*	-0.206**	-0.068*
	(48.341)	(0.013)	(0.009)	(0.005)	(0.089)	(0.038)
Firms	162.748	-0.048	-0.024	-0.023	0.115	0.083
	(128.030)	(0.054)	(0.033)	(0.023)	(0.083)	(0.070)
InfoTrade*Firms	66.882	0.012	0.009	0.002	0.052	0.001
	(60.108)	(0.019)	(0.014)	(0.006)	(0.109)	(0.047)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	8,123	8,464	8,463	8,464	7,648	8,221

Table A2

Conditioning on Signal Strength

This table presents the results conditioning on the strength of the information tip received by the trader. The dependent variables are information signals. **Panel A** reports the results for stock-based signals, **Panel B** the results for option-based signals, and **Panel C** the results for mixed signals. The variable InfoTrade is an indicator variable equal to one for days of insider trading activity and zero for trading window 35-21 days prior to the first insider trading date in each firm. We exclude all trades that occur within three trading days prior to public information release. All definitions of the control variables, measured at the daily frequency, mirror those in Table II. All panels include firm and time fixed effects and additionally adjust the information signals, subtracting average values of the portfolio of matched firms. The matching is performed along two-digit SIC industry codes and the same market capitalization quintile. Standard errors (in parentheses) are clustered around firms. ***, **, * denote 1%, 5%, and 10% level of statistical significance, respectively.

Based on			**Prices**			**Volume**		**Both**	
	Quoted Spread	Price Impact	Price Range	Realized Volatility	Price Inform.	Order Imb.	Abn. Volume	Lambda	Illiq.
				Panel A: Stock-based signals					
InfoTrade	-0.075***	-0.066	0.697***	-0.028	29.156	-0.007*	134.500	-0.026***	-0.194*
	(0.022)	(0.432)	(0.173)	(0.037)	(20.986)	(0.004)	(148.793)	(0.008)	(0.106)
Strength	-0.000	0.004	-0.004***	-0.002**	-0.297**	0.000	-1.458*	0.001***	0.001
	(0.001)	(0.012)	(0.001)	(0.001)	(0.148)	(0.000)	(0.774)	(0.000)	(0.001)
InfoTrade*Strength	0.001	0.000	0.004	0.001	0.186	-0.000	0.721	0.000*	-0.003*
	(0.001)	(0.009)	(0.003)	(0.001)	(0.227)	(0.000)	(1.319)	(0.000)	(0.002)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	10,905	10,859	10,930	10,165	9,096	10,859	10,905	10,845	10,873
	Quoted Spread (all)	Quoted Spread (otm)	IV Calls	IV Puts	IV Skew	Abn. Volume	Volume Ratio (otm/all)	Illiq.	
				Panel B: Option-based signals					
InfoTrade	-0.049***	-0.080***	0.025***	0.020**	0.005*	1,384.973**	-2.485	-0.071**	
	(0.019)	(0.024)	(0.008)	(0.009)	(0.003)	(535.214)	(1.868)	(0.033)	
Strength	0.001***	0.001***	-0.000	-0.000	-0.000	0.139	0.034***	0.000	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(1.882)	(0.010)	(0.001)	
InfoTrade*Strength	0.000	0.000	0.000	0.000	-0.000	-2.852	-0.028	-0.001	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(3.272)	(0.021)	(0.001)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
#Obs	7,372	7,372	7,273	7,134	7,070	7,454	7,464	6,606	

TABLE A2
Conditioning on Signal Strength

Based on	**Prices**		**Volume**			**Both**
			Panel C: Mixed Market Signals			
	Quoted Spread Ratio	Volume Ratio O/S	Volume Ratio Calls/S	Volume Ratio Puts/S	Illiq. S/O	Illiq. O/S
InfoTrade	-34.997	0.060***	0.047***	0.011***	-0.088**	-0.219***
	(34.797)	(0.010)	(0.008)	(0.004)	(0.034)	(0.061)
Strength	0.021	-0.000***	-0.000***	-0.000***	-0.000	0.002***
	(0.124)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
InfoTrade*Strength	0.446	-0.000	-0.000	0.000	0.000	-0.000
	(0.331)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	7,157	7,464	7,463	7,464	7,243	6,691

Table A3
Conditioning on Event Type

This table presents separate results for M&As and earnings announcements. The dependent variables are information signals. **Panels A and B** report the results for stock-based signals, **Panels C and D** the results for option-based signals, and **Panels E and F** the results for mixed signals. The variable InfoTrade is an indicator variable equal to one for days of insider trading activity and zero for trading window 35-21 days prior to the first insider trading date in each firm. We exclude all trades that occur within three trading days prior to public information release. All definitions of the control variables, measured at the daily frequency, mirror those in Table II. All panels include firm and time fixed effects and additionally adjust the information signals, subtracting average values of the portfolio of matched firms. The matching is performed along two-digit SIC industry codes and the same market capitalization quintile. Standard errors (in parentheses) are clustered around firms. ***, **, * denote 1%, 5%, and 10% level of statistical significance, respectively.

Based on			**Prices**			**Volume**		**Both**	
Panel A: Stock-based signals									
	Quoted Spread	Price Impact	Price Range	Realized Volatility	Price Inform.	Order Imb.	Abn. Volume	Lambda	Illiq.
Panel A: Stock-based Signals: Mergers and Acquisitions									
InfoTrade	-0.014	0.408	0.617***	0.050*	12.124	-0.010**	174.507**	-0.002	-0.398***
	(0.020)	(0.452)	(0.130)	(0.027)	(22.077)	(0.005)	(82.158)	(0.006)	(0.105)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	6,605	6,558	6,674	5,999	5,323	6,558	6,653	6,546	6,611
Panel B: Stock-based Signals: Earnings Announcements									
InfoTrade	-0.026	-0.355	0.089	-0.077*	35.851	0.001	-426.836	-0.031	-0.019
	(0.019)	(0.627)	(0.371)	(0.041)	(55.622)	(0.007)	(541.048)	(0.020)	(0.029)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	1,769	1,769	1,769	1,726	1,594	1,769	1,769	1,769	1,769
	Quoted Spread (all)	Quoted Spread (otm)	IV Calls	IV Puts	IV Skew	Abn. Volume	Volume Ratio (otm/all)	Illiq.	
Panel C: Option-based Signals: Mergers and Acquisitions									
InfoTrade	-0.036	-0.082***	0.029***	0.024**	0.005**	935.148***	-5.095**	-0.113***	
	(0.023)	(0.031)	(0.009)	(0.011)	(0.003)	(336.360)	(2.199)	(0.028)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
#Obs	4,478	4,478	4,403	4,302	4,279	4,495	4,499	3,866	
Panel D: Option-based Signals: Earnings Announcements									
InfoTrade	-0.008	-0.016	0.017*	0.006	0.000	1,143.200	3.666	-0.107**	
	(0.034)	(0.044)	(0.010)	(0.010)	(0.004)	(1,674.541)	(3.308)	(0.052)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
#Obs	1,547	1,547	1,610	1,590	1,439	1,616	1,616	1,534	

Table A3
Conditioning on Event Type (Continued)

Based on	**Prices**	**Volume**			**Both**	
	Quoted Spread Ratio	Volume Ratio O/S	Volume Ratio Calls/S	Volume Ratio Puts/S	Illiq. S/O	Illiq. O/S
Panel E: Mixed-market Signals: Mergers and Acquisitions						
InfoTrade	-41.299	0.061***	0.050***	0.007*	-0.204***	-0.068*
	(43.370)	(0.015)	(0.011)	(0.004)	(0.077)	(0.035)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	4,370	4,499	4,499	4,499	3,912	4,383
Panel F: Mixed-market Signals: Earnings Announcements						
InfoTrade	-16.950	0.038***	0.023**	0.015**	-0.237**	-0.108**
	(74.437)	(0.011)	(0.009)	(0.007)	(0.106)	(0.047)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	1,499	1,616	1,616	1,616	1,537	1,607

Table A4
Volume Ratios: Maturity and Moneyness

The dependent variables are Volume Ratios defined as the ratio of option volume to the stock volume measured at daily level over the period 1995–2015. **Panel A** reports the results for a specification with firm and time fixed effects**. Panel** B reports the results for control-adjusted Volume Ratios, i.e., subtracting average values of the portfolio of matched firms. The matching is performed along two-digit SIC industry codes and the same market capitalization quintile. The variable InfoTrade is an indicator variable equal to one for days of insider trading activity and zero for trading window 35-21 days prior to the first insider trading date in each firm. We exclude all trades that occur within three trading days prior to public information release. All definitions of the control variables, measured at the daily frequency, mirror those in Table II. Standard errors (in parentheses) are clustered around firms. ***, **, * denote 1%, 5%, and 10% level of statistical significance, respectively.

	Maturity				Moneyness		
	<10d	10-30d	31-60d	>60d	ITM	ATM	OTM
Panel A: Volume ratio O/S with time and firm fixed effects							
InfoTrade	0.007**	0.022***	0.022***	0.003	0.006***	0.009***	0.040***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.002)	(0.003)	(0.006)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	8,488	8,488	8,488	8,488	8,488	8,488	8,488
Panel B: Volume ratio O/S with time and firm fixed effects (control group adjusted)							
InfoTrade	0.006**	0.021***	0.021***	0.002	0.005***	0.009***	0.038***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.002)	(0.003)	(0.006)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	8,488	8,488	8,488	8,488	8,488	8,488	8,488

Table A5

Conditioning on Information Direction

This table presents separate results for positive and negative information events. The dependent variables are information signals. **Panels A and B** report the results for stock-based signals, **Panels C and D** the results for option-based signals, and **Panels E and F** the results for mixed signals. The variable InfoTrade is an indicator variable equal to one for days of insider trading activity and zero for trading window 35-21 days prior to the first insider trading date in each firm. We exclude all trades that occur within three trading days prior to public information release. All definitions of the control variables, measured at the daily frequency, mirror those in Table II. All panels include firm and time fixed effects and additionally adjust the information signals, subtracting average values of the portfolio of matched firms. The matching is performed along two-digit SIC industry codes and the same market capitalization quintile. Standard errors (in parentheses) are clustered around firms. ***, **, * denote 1%, 5%, and 10% level of statistical significance, respectively.

Based on			**Prices**			**Volume**		**Both**	
	Quoted Spread	Price Impact	Price Range	Realized Volatility	Price Inform.	Order Imb.	Abn. Volume	Lambda	Illiq.
				Panel A: Stock-based Signals: Positive News					
InfoTrade	-0.012	0.381	0.774***	0.048**	31.169	-0.007*	150.824	-0.005	-0.323***
	(0.017)	(0.384)	(0.126)	(0.022)	(20.094)	(0.004)	(100.484)	(0.005)	(0.084)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	8,807	8,758	8,906	8,151	7,322	8,758	8,882	8,746	8,839
				Panel B: Stock-based Signals: Negative News					
InfoTrade	-0.106**	-1.039	0.840**	-0.073**	43.613	-0.013*	265.312	-0.042**	-0.171
	(0.043)	(0.648)	(0.333)	(0.032)	(43.850)	(0.007)	(317.542)	(0.017)	(0.223)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	3,324	3,323	3,356	3,153	2,841	3,323	3,355	3,320	3,348
	Quoted Spread (all)	Quoted Spread (otm)	IV Calls	IV Puts	IV Skew	Abn. Volume	Volume Ratio (otm/all)	Illiq.	
				Panel C: Option-based Signals: Positive News					
InfoTrade	-0.024	-0.050**	0.035***	0.029***	0.007**	1,159.844***	-3.916**	-0.092***	
	(0.018)	(0.023)	(0.008)	(0.009)	(0.003)	(435.896)	(1.885)	(0.025)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
#Obs	6,191	6,191	6,118	5,996	5,892	6,259	6,266	5,491	
				Panel D: Option-based Signals: Negative News					
InfoTrade	-0.025	-0.056	0.009	0.011	-0.003	1,025.975	-0.826	-0.044**	
	(0.031)	(0.049)	(0.013)	(0.013)	(0.003)	(989.573)	(2.546)	(0.020)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
#Obs	2,166	2,166	2,135	2,117	2,089	2,180	2,183	2,057	

Table A5
Conditioning on Information Direction

Based on	**Prices**	**Volume**			**Both**	
	Quoted Spread Ratio	Volume Ratio O/S	Volume Ratio Calls/S	Volume Ratio Puts/S	Illiq. S/O	Illiq. O/S
			Panel E: Mixed-market Signals: Positive News			
InfoTrade	-10.332	0.062***	0.050***	0.010***	-0.202***	-0.075***
	(35.544)	(0.011)	(0.008)	(0.003)	(0.065)	(0.029)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	6,017	6,266	6,265	6,266	5,572	6,094
			Panel F: Mixed-market Signals: Negative News			
InfoTrade	-77.471	0.025***	0.012*	0.013**	-0.076	-0.029*
	(67.770)	(0.009)	(0.006)	(0.006)	(0.051)	(0.018)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	2,091	2,183	2,183	2,183	2,076	2,127

Table A6
Volume Ratios Net of Insider Trades

The dependent variables are Volume Ratios net of insider traders' trades, measured at the firm and daily level over the period 1995–2015. The variable InfoTrade is an indicator variable equal to one for days of insider trading activity and zero for trading window 35-21 days prior to the first insider trading date in each firm. We exclude all trades that occur within three trading days prior to public information release. All definitions of the control variables, measured at the daily frequency, mirror those in Table II. All panels include firm and time fixed effects and additionally adjust the information signals, subtracting average values of the portfolio of matched firms. The matching is performed along two-digit SIC industry codes and the same market capitalization quintile. Standard errors (in parentheses) are clustered around firms. ***, **, * denote 1%, 5%, and 10% level of statistical significance, respectively.

	Volume Ratio O/S	Volume Ratio Calls/S	Volume Ratio Puts/S
InfoTrade	0.045***	0.034***	0.010***
	(0.008)	(0.006)	(0.003)
Controls	Yes	Yes	Yes
#Obs	8,488	8,487	8,488

Table A7
Conditioning on Market Capitalization

This table presents separate results for small and large stock market capitalization. The dependent variables are information signals. **Panels A and B** report the results for stock-based signals, **Panels C and D** the results for option-based signals, and **Panels E and F** the results for mixed signals. The variable InfoTrade is an indicator variable equal to one for days of insider trading activity and zero for trading window 35-21 days prior to the first insider trading date in each firm. We exclude all trades that occur within three trading days prior to public information release. All definitions of the control variables, measured at the daily frequency, mirror those in Table II. All panels include firm and time fixed effects and additionally adjust the information signals, subtracting average values of the portfolio of matched firms. The matching is performed along two-digit SIC industry codes and the same market capitalization quintile. Standard errors (in parentheses) are clustered around firms. ***, **, * denote 1%, 5%, and 10% level of statistical significance, respectively.

Based on			**Prices**			**Volume**		**Both**	
	Quoted Spread	Price Impact	Price Range	Realized Volatility	Price Inform.	Order Imb.	Abn. Volume	Lambda	Illiq.
				Panel A: Stock-based Signals: Small caps					
InfoTrade	-0.084**	-0.250	1.246***	0.020	73.700*	-0.023***	101.654	-0.030**	-0.642***
	(0.035)	(0.734)	(0.226)	(0.040)	(38.916)	(0.007)	(62.683)	(0.012)	(0.177)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	6,134	6,084	6,249	5,324	4,326	6,084	6,227	6,068	6,174
				Panel B: Stock-based Signals: Large caps					
InfoTrade	0.000	0.289*	0.324***	0.018	7.834	0.004	207.715	-0.002*	0.012
	(0.005)	(0.173)	(0.106)	(0.015)	(18.542)	(0.003)	(193.649)	(0.001)	(0.009)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	6,012	6,012	6,028	5,995	5,849	6,012	6,025	6,013	6,028
	Quoted Spread (all)	Quoted Spread (otm)	IV Calls	IV Puts	IV Skew	Abn. Volume	Volume Ratio (otm/all)	Illiq.	
				Panel C: Option-based Signals: Small caps					
InfoTrade	-0.039	-0.091***	0.053***	0.034*	0.010	676.815***	-3.102	-0.132**	
	(0.031)	(0.034)	(0.018)	(0.017)	(0.007)	(219.865)	(3.476)	(0.055)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
#Obs	2,930	2,930	2,740	2,616	2,742	2,924	2,931	2,247	
				Panel D: Option-based Signals: Large caps					
InfoTrade	-0.034**	-0.051*	0.017***	0.017**	0.003	1,406.927**	-2.813*	-0.068***	
	(0.017)	(0.026)	(0.006)	(0.008)	(0.002)	(597.047)	(1.688)	(0.020)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
#Obs	5,442	5,442	5,513	5,498	5,254	5,530	5,533	5,301	

Table A7
Conditioning on Market Capitalization

Based on	**Prices**		**Volume**		**Both**	
	Quoted Spread Ratio	Volume Ratio O/S	Volume Ratio Calls/S	Volume Ratio Puts/S	Illiq. S/O	Illiq. O/S
Panel E: Mixed-market Signals: Small caps						
InfoTrade	-13.887	0.060***	0.043***	0.013**	-0.430***	-0.183**
	(20.482)	(0.017)	(0.013)	(0.006)	(0.141)	(0.072)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	2,877	2,931	2,930	2,931	2,323	2,723
Panel F: Mixed-market Signals: Large caps						
InfoTrade	-37.738	0.052***	0.042***	0.009**	-0.092*	-0.022**
	(43.901)	(0.011)	(0.008)	(0.003)	(0.053)	(0.009)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	5,246	5,533	5,533	5,533	5,325	5,498

Table A8
Conditioning on Market Capitalization: Whistleblower's Sub-sample

This table presents separate results for small and large stock market capitalization. The trades correspond to those in the Whistleblower Reward Program subsample. The dependent variables are information signals. **Panels A and B** report the results for stock-based signals, **Panels C and D** the results for option-based signals, and **Panels E and F** the results for mixed signals. The variable InfoTrade is an indicator variable equal to one for days of insider trading activity and zero for trading window 35-21 days prior to the first insider trading date in each firm. We exclude all trades that occur within three trading days prior to public information release. All definitions of the control variables, measured at the daily frequency, mirror those in Table II. All panels include firm and time fixed effects and additionally adjust the information signals, subtracting average values of the portfolio of matched firms. The matching is performed along two-digit SIC industry codes and the same market capitalization quintile. Standard errors (in parentheses) are clustered around firms. ***, **, * denote 1%, 5%, and 10% level of statistical significance, respectively.

Based on			**Prices**				**Volume**		**Both**
	Quoted Spread	Price Impact	Price Range	Realized Volatility	Price Inform.	Order Imb.	Abn. Volume	Lambda	Illiq.
Panel A: Stock-based Signals: Small caps									
InfoTrade	-0.073**	-0.126	1.325***	0.049	32.276	-0.025***	154.033	-0.063***	-0.337**
	(0.030)	(1.039)	(0.304)	(0.041)	(41.584)	(0.008)	(120.072)	(0.019)	(0.142)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	3,353	3,351	3,395	3,317	3,032	3,351	3,394	3,351	3,379
Panel B: Stock-based Signals: Large caps									
InfoTrade	0.006	-0.064	0.031	0.002*	-46.090**	-0.004	277.738	-0.001	0.010
	(0.005)	(0.266)	(0.150)	(0.001)	(19.277)	(0.004)	(235.612)	(0.001)	(0.017)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	3,054	3,054	3,054	3,051	3,022	3,054	3,054	3,054	3,054

	Quoted Spread (all)	Quoted Spread (otm)	IV Calls	IV Puts	IV Skew	Abn. Volume	Volume Ratio (otm/all)	Illiq.
Panel C: Option-based Signals: Small caps								
InfoTrade	-0.073	-0.128***	0.092***	0.059**	0.022	953.654**	-6.697	-0.190**
	(0.049)	(0.044)	(0.027)	(0.027)	(0.014)	(420.077)	(4.632)	(0.082)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	1,993	1,993	1,822	1,707	1,787	1,991	1,994	1,497
Panel D: Option-based Signals: Large caps								
InfoTrade	-0.078**	-0.125**	0.019**	0.033***	0.002	1,064.789	-2.265	-0.066*
	(0.031)	(0.051)	(0.008)	(0.009)	(0.003)	(759.945)	(3.362)	(0.039)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	2,768	2,768	2,847	2,858	2,598	2,859	2,859	2,770

Table A8 (Continued)
Conditioning on Market Capitalization: Whistleblower's Sub-sample

Based on	Prices	Volume			Both	
	Quoted Spread Ratio	Volume Ratio O/S	Volume Ratio Calls/S	Volume Ratio Puts/S	Illiq. S/O	Illiq. O/S
Panel E: Mixed-market Signals: Small caps						
InfoTrade	-9.479	0.094***	0.062***	0.029***	-0.492**	-0.313***
	(34.588)	(0.027)	(0.020)	(0.011)	(0.209)	(0.089)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	1,982	1,994	1,993	1,994	1,558	1,808
Panel F: Mixed-market Signals: Large caps						
InfoTrade	-98.329	0.049***	0.036***	0.013**	-0.053	-0.032
	(95.805)	(0.015)	(0.011)	(0.006)	(0.106)	(0.021)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	2,714	2,859	2,859	2,859	2,780	2,839

Table A9
Conditioning on Option Availability

This table presents results for stocks that have listed options. The dependent variables are information signals. The variable InfoTrade is an indicator variable equal to one for days of insider trading activity and zero for trading window 35-21 days prior to the first insider trading date in each firm. We exclude all trades that occur within three trading days prior to public information release. All definitions of the control variables, measured at the daily frequency, mirror those in Table II. All panels include firm and time fixed effects and additionally adjust the information signals, subtracting average values of the portfolio of matched firms. The matching is performed along two-digit SIC industry codes and the same market capitalization quintile. Standard errors (in parentheses) are clustered around firms. ***, **, * denote 1%, 5%, and 10% level of statistical significance, respectively.

Based on	Prices					Volume		Both	
	Quoted Spread	Price Impact	Price Range	Realized Volatility	Price Inform.	Order Imb.	Abn. Volume	Lambda	Illiq.
InfoTrade	-0.002	0.222	0.492***	0.004	35.278*	0.001	171.343	-0.010***	-0.005
	(0.012)	(0.248)	(0.116)	(0.012)	(20.882)	(0.003)	(138.815)	(0.004)	(0.011)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	8,430	8,431	8,464	8,287	7,916	8,431	8,457	8,431	8,464