Chasing Private Information*

Marcin Kacperczyk† and Emiliano S. Pagnotta‡

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Abstract

Do public trade signals (volume and asset prices) reveal the presence of privately informed investors? What signals are most reliable in this regard? We examine these issues using a novel sample of over 5,000 equity and option trades based on material and nonpublic information documented in the Securities and Exchange Commission's (SEC) insider trading litigation files. We find that information embedded in equity (option) markets offers a generally weaker (stronger) signal of private information. Days when informed investors trade display, both in stock and option markets, abnormally high volatility and volume and low illiquidity. The most consistent signals combine both option and stock volume, especially the volume of leveraged and short-term options. We exploit the implementation of the SEC's Whistleblower Program to assess the validity of our approach against selection bias. Overall, our results provide new guidance in the search for private information.

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†Imperial College London and CEPR. Email: m.kacperczyk@imperial.ac.uk

‡Imperial College London. Email: e.pagnotta@imperial.ac.uk

1 Introduction

Asymmetric information is ubiquitous in economics and finance. In a world with asymmetric information, market participants want to know when informed investors trade when deciding about their own trades. 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 signals may provide useful guidance in the quest for private information, it is difficult to assess empirically how much information they truly reveal because information sets are almost never observable. For example, changing levels of prices may reflect time-varying risk premia. Similarly, changing levels of volume may be due to a systematic liquidity component or uninformed demand pressure.[2]

In this paper, we consider a novel setting–insider trading investigations–to directly evaluate the ability of market signals to reveal private information. Specifically, we hand-collect a comprehensive sample of insider trading investigations by the SEC which document in detail how certain individuals trade on nonpublic and material information. Our sample of SEC cases involves a large number of trades in several hundred companies over the period 1995-2015. The advantage of using insider trading data is that we can observe the dynamics of market signals at times when private information is used and, therefore, we can assess their ability to identify private information. Our ability to observe private information directly comes in stark contrast to prior literature that typically infers the presence of informed trading indirectly, either by observing the trading behavior of financial professionals (e.g., institutional investors or large activist shareholders) or 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 types of information signals: (i) those based on stock data, (ii) those based on option data, and (iii) those combining stocks

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

[2]Moreover, most theory-motivated information measures, 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 not only infer whether bad or good news arrive, but the arrival of news in the first place (e.g., Easley and O'Hara, 1992; Banerjee and Green, 2015).

and options. For each signal, we analyze the importance of prices, volume, or the combination of the two. Our results carry three main messages: (1) options markets generally reveal more information about informed trading than does equity market; (2) informed trading is more likely detected when volume is jointly used with prices; (3) the most robust public signals utilize information that spans both option and stock markets.

Our empirical tests make use of 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 exploiting material and nonpublic information. For example, a family member of a given company's CFO may privately learn about exceptionally high quarterly earnings and acquire shares of the company in advance of a company's earnings report. We collect detailed information about the motivating private information, the individual traders, the assets and exact dates of the trade, and all available details about the executed trade execution (e.g., prices and quantities). We additionally collect information about the dates when the motivating private information is released to the market. Importantly, we emphasize that there is no uncertainty on whether the underlying information is private in our setting. Overall, the final sample contains 5,058 trades in 615 companies that represent the vast majority of industry sectors.

At the outset, we evaluate the strength of the private signals that traders in our sample base their trades on. We do so by computing hypothetical stock returns (excluding dividends) a trader would realize if she initiated her trade at the opening price of the day the informed trader trades first, and she 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 positive sign and 20% for those of negative sign. Both results are economically large, especially since they accrue over a relatively short window of 7 days on average. In fact, these figures may underestimate the pre-fees profits of the informed traders as 30% of trades are executed using options, not stocks.

Our main empirical tests aim to establish whether various measures of information display abnormal behavior on days when insiders are trading. In particular, we utilize an event-study framework, in which we compare the values of information measures for companies traded by informed investors, on the days they trade, to the values recorded for such companies on days preceding the informed trades. Specifically, we consider a 15-day pre-event window that spans 21 to 35 trading days prior to insider trading day. We additionally exclude all events related to earnings announcements that take place within three trading days of the public release. Imposing such restrictions mitigates possible serial correlation in information measures and addresses the concern that other traders might speculate on the direction of the news around the scheduled corporate event day.

Our statistical approach is based on the regression model with various information measures as dependent variables and the indicator variable, $TRADE$, equal to one on the insider trading day and equal to zero on the selected 15 days, as a main independent variable. Our information measures are constructed using three types of signals: (a) price; (b) volume; and (c) price and volume together, and span both equity and option markets. To soak up the variation in our dependent variable, we include the natural logarithm of market equity, stock volatility, turnover, and stock price as controls. All controls are pre-determined and measured at the beginning of the control window. We hypothesize that the coefficient of $TRADE$ should be statistically significant if a particular measure reveals private information.

Our results indicate that information measures that are solely based on stock signals generally do not reveal private information to markets. Of the seven measures we consider, only two–daily illiquidity and price range–are statistically significant in the most comprehensive model that includes both firm and time-fixed effects and benchmarks the affected companies against a portfolio of firms in the same 2-digit SIC industry with a similar market capitalization. Further, illiquidity is negatively related to instances of informed trading, in line with the results document in a recent paper by Collin-Dufresne and Fos (2015) for the sample of activist investors. Next, we entertain similar tests for measures derived from options data. We find that, on average, option-based measures are more indicative of informed trading. Six out of seven measures we consider are statistically significant in the most comprehensive specification. The most significant measures include implied volatility, the bid–ask spread of levered options, and an analogous illiquidity measure. Finally, we consider mixed measures, those combining data from both stock and option markets. Our most significant measures are those that relate option volume to the corresponding equity volume, either for all types of contracts, or calls and puts taken separately. Also significant are measures that capture cross-liquidity effects between stock and option markets. Overall, our results suggest a strong information content of signals coming from option markets. This result is particularly interesting since prior research has mostly focused on stock-based measures to identify the presence of informed trading.

Since our sample consists solely of SEC-investigated insider trading violations, one might be concerned about a sample selection bias. In particular, an important selection concern would be that insider traders get exposed *only* when information measures display abnormal values.[3] In this case, one would overestimate the information measures' capacity to detect information. Our results do not support this hypothesis. First, evidence based on prior work by Meulbroek (1992) as well as our own conversations with the regulators suggest that a large fraction of investigations is initiated not as a result of 'active screening' by the SEC but, rather, based on external tips that regulators receive. Second, if one believes that the SEC successfully acts upon screening measures of stock market activity, one would have to explain why almost all stock-based measures fail to detect informed trading in our sample.[4] Third, both stock-based and option-based illiquidity measures move in the opposite direction to what informed trading models would have predicted. They display lower values when insider trading takes place. This finding would then imply that the SEC is particularly sensitive to illegal trading activity when markets look orderly and abnormally liquid.

To further assess the validity of our approach against selection bias, we design specific tests that are discussed with more detail in Section 4.3. First, we take advantage of the 2010 adoption of the SEC Whistleblower Program, which offers monetary rewards to individuals that provide useful tips to uncover illegal insider trading. Second, we split the full sample into cases that are, conceptually speaking, less likely to be subject to bias from the remainder. We start by following Meulbroek's idea that cases that involve a large number of firms are less likely to originate in detection based on trading patterns. We design similar tests based on the 'complexity' of the trading schemes. The results of all of these tests strongly suggest that the origin of the investigation does not drive our main results.

We conduct a number of additional tests. First, we study cross-sectional determinants of information measures utilizing volume from options and stocks markets. Our results are strongest for measures 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 may relief capital constraints (Black, 1975). Second, we show that

[3]An alternative hypothesis is that the SEC investigation causes certain measures to be informative. But this is, of course, not possible since the investigation always happens after the fact, on average 2 years after (Augustin et al. (2015)).

[4]In our sample, over 70% of trades are executed using stocks.

aggregate insider trading constitutes an economically significant share of the total traded volume in both stock and options. We further show that, while greater informed volume fractions strengthen our results, they do not alter their qualitative nature. Third, we show that our main results are generally robust to measures of trader sophistication. Fourth, we find that stock-based and option-based measures reveal more information ahead of unscheduled events, such as mergers and acquisitions, compared to scheduled events, such as earnings announcements. In turn, mixed-market measures offer equally strong signals ahead of both types of events. Finally, market signals reveal more information in anticipation of positive news than negative news.

Related Literature

Our paper spans three strands of literature. First, we contribute to the literature on the informational content of stock and option prices. Theoretical literature has identified links between private information and liquidity of stocks (e.g., Glosten and Milgrom, 1985; Kyle, 1985; Easley and O'Hara, 1987), liquidity of options (e.g., Biais and Hillion, 1994; Easley et al., 1998), volatility of stock prices (e.g., Wang, 1993), and volatility of options (e.g., Back, 1993). Our information measure candidates are motivated by this literature and the corresponding empirical work.[5] Yet, empirically, we know little about how much information is revealed in such measures, which is the main focus of our paper. A notable exception is recent work by Collin-Dufresne and Fos (2015) and Collin-Dufresne et al. (2015) who identify a negative (positive) relationship between trading behavior of activist investors and measures of adverse selection for stocks (options), which they attribute to strategic behavior of such investors. Our results from stock data are consistent with their results; at the same time, the conclusions we draw from the option data are opposite. One way to reconcile the apparent differences is that, unlike our traders, activist investors do not trade much in options, possibly because they do not trade motivated by corporate events but, rather, on their perceived ability to 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 model or PIN (Easley et al. (1996a,b)). The information struc-

[5] Biais et al. (2005) and Vayanos and Wang (2013), among others, provide thorough reviews of the theoretical literature.Hasbrouck (2007), Goyenko et al. (2009) and Holden et al. (2014), among others, survey the empirical literature.

ture of the model has been adopted and extended by Easley et al. (2008) and Duarte and Young (2009). Odders-White and Ready (2008) extend a Kyle-type model and allow for the amount of information to be separated from the probability of arrival. Common to most of these papers is the assumption that informed traders do not respond to price changes. In contrast, Back et al. (2016) analyses a model with a PIN-like information structure but where a single informed trader acts strategically, as in Back (1992), and conclude that private information cannot be identified using order flow alone.[6] Boulatov et al. (2013) and Hendershott et al. (2015) identify information based on institutional order flow. Kacperczyk et al. (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 asset managers (e.g., Kacperczyk and Seru, 2007; Cohen et al., 2008; and Kacperczyk et al., 2014), corporate insiders (Cohen et al. (2012)), or activist investors (Collin-Dufresne and Fos (2015), Collin-Dufresne et al. (2015)). 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 profitability of trades prior to earnings announcements. Augustin et al. (2015) study option trading prior to M&A activity and test whether abnormal trade volume is linked to private information by means of predicting subsequent M&A events. While all the above approaches have merit, ultimately they are unable to provide a definite 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 by Koudijs (2015) and Koudijs (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 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.[7] Meulbroek (1992) examines the impact of illegal trading on stock returns and market efficiency using a sample of legal cases from the 1980s. She shows that insider trades affect returns as predicted by standard theory. Cornell and Sirri

[6] A number of papers analyze the performance of the PIN model. See, among others, Aktas et al. (2007), Brennan et al. (2015), and Duarte et al. (2015).

[7] Bhattacharya (2014) provides an excellent review of the literature on both legal and illegal insider trading.

Table I
The Matrix of Signals

Signal/Market	**Stocks**	**Stock options**	**Both**
Price-based	Quote spreads RV Price Impact	Quote spreads IV	Spread ratios
Volume-based	Abnormal vol Order imbalance	Abnormal vol	Volume ratios
Price- & volume-based	Illiquidity Lambda	Illiquidity	Illiquidity ratios

(1992) present a single company case study of the impact of insider trading on stock liquidity. More recently, Del Guercio et al. (2013) study the effect of time-varying legal enforcement environment on price discovery.[8]

The rest of the paper proceeds as follows. In Section 2, we discuss the theories motivating the information measures candidates and our empirical implementation. Section 3 describes the sample of insider trading cases. In Section 4, we present our main empirical results. Section 4.3 discusses selection bias. Section 5 concludes.

2 Signals of Information-Based Trading

In this section, we summarize various signals that we use as candidates to identify private information. Our choice of the signals is dictated by related theoretical models as well as their popularity in empirical studies. Sections 2.1 and 2.2 discuss the connections between theories of informed trading in stock and derivative markets and the behavior of the information measures candidates as well as our empirical implementation. For clarity of exposition, we make a distinction between signals that are purely based on stock data, option data, or both. Further, within each asset class, we group measures according to whether they are based on prices, volume, or a combination of these. When considering a particular measure, the subindex s (o) denotes stock (option) data. Table I summarizes the main signals we consider using this classification. Further details on the construction of the data are discussed in Section 2.4.

[8]From a different perspective, Ahern (2015) provides a description of insider trading networks.

2.1 Private Information in Stock Markets

In competitive models of privately informed traders (e.g., Grossman and Stiglitz (1980); Hellwig (1980); Admati (1985); Blume et al. (1994); Easley and O'Hara (2004), for stock markets; Brennan and Cao (1996), for option markets), prices and volume are jointly determined as a function of the fraction of informed traders and their information precision. Because each investor is infinitesimal, 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, instead, typically consider some form of imperfect competition in the use of information.

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 O'Hara (1987) extend this model and show that the prices that market makers post depend on the size of the order. We then naturally measure 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.

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 the impact they have on the price and the less it can deviate from fundamentals (e.g., Friedman (1953); De Long et al. (1990); Campbell and Kyle (1993)). However, other papers argue that the relation is not straightforward (e.g., de Long et al. (1990)). Wang (1993) explicitly analyzes a dynamic asset pricing model with asymmetric information and risk-averse agents. He finds that the effect on returns and volatility is ambiguous. On the one hand, the presence of traders with superior information induces uninformed traders demand a larger premium for the adverse selection risk. However, 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 two specific measures: the daily price range and the realized variance.

Next, we formally define the considered stock price-based measures.

Quoted Spread (QS) 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

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

where b and a denote the best bid and offer quotes (BBO), $m \equiv \frac{1}{2}(a+b)$ 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 ($\boldsymbol{PI}$) Finally, the five-minute price impact is given by

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

where m_{k+5} is the midpoint of the consolidated BBO 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 measure represents the permanent component of the effective spread and, intuitively, it measures gross losses of liquidity demanders due to adverse selection costs.[9]

Price Range ($\boldsymbol{PR}$) We define the daily price range simply as

$$PR_{s,t} = \frac{a_{\max,t} - b_{\min,t}}{\text{Average}},$$

where $a_{\mathrm{max,t}}$ and $b_{\mathrm{min,t}}$ denote the maximum offer price and the minimum bid price on day t. *Average* is the arithmetic average of the two quantities. PR can be seen both as a measure of price dispersion and of liquidity. Corwin and Schultz (2012) show how the the high and low daily prices relate to the intraday bid–ask spread and volatility.

Realized Variance ($\boldsymbol{RV}$) We also consider the standard realized variance (RV) specification (e.g., Barndorff-Nielsen and Shephard (2002)) based on 30-minute intervals.

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

Volume-based Signals

Easley and O'Hara (1992) pioneered the role of volume as a measure of adverse selection. In contrast to Kyle (1985) and Glosten and Milgrom (1985), liquidity providers in this model need not only learn both about the sign of private information, but about the occurrence of private information in the first place. 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 probability of informed trading (PIN) empirical framework, which aims at measuring the adverse selection risk faced by uninformed traders.[10] We follow Easley et al. (2008) and use the absolute order imbalance an alternative measure of the PIN, which has two distinct advantages. First, it can be computed over short time periods like a day. Second, it does not have the numerical overflow problems that can be encountered when computing the PIN log-likelihood function.

Next, we formally define the considered stock volume-based measures.

Absolute order imbalance ($\boldsymbol{AOI}$) 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 number of buys and the number of sells, respectively, over a given trading day t.

Price- and Volume-based Measures

The imperfect competition model of Kyle (1985) predicts that the presence of a single informed trader will 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 et al. (2000)). Trading volume and returns are also related in

[10]Interestingly, Banerjee and Green (2015) suggests that the relationship between the occurrence of information events and 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.

a model with risk-averse agents of Wang (1994). As information asymmetry increases, uninformed investors demand a larger price discount when they buy the stock from informed investors in order to cover the risk of trading against private information. Therefore, trading volume is positively correlated with absolute price changes and this correlation becomes stronger when there is more asymmetric information. 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:

$$Lambda_s \text{ (slope): } r_n = \lambda \times (\sum_k d_k \sqrt{|vol_k|})_n + \text{error}_n$$

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 results based on 30-minute intervals.[11]

Daily Illiquidity (DI) For a given day t, DI is given by the ratio between the absolute price return to dollar volume

$$DI_{s,t} = \frac{|r_t|}{vol_t}.$$

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 an average of DI over a period of time.

2.2 Private Information in Option Markets

It is rather intuitive that privately informed agents may 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 that we discussed in Section 2.1 are also useful in the analysis of options, we further consider insights from a (relatively small) literature that has explicitly considered equilibrium models

[11] We also computed *Lambda* and the realized variance based on 5-minute intervals, obtaining similar results.

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.

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. They find that, consistent with economic intuition, asymmetric information increases options bid–ask spread. The same relation arises in the related model by John and Subrahmanyam (2003).

Less obvious is the effect of asymmetric information on implied volatility (IV). Suppose an informed trader receives good news about a firm. At face value, if she increases total demand for, say, call options, the associated IV will increase. But this simple connection does not take into account how uninformed traders will react in equilibrium (as Biais and Hillion (1994) point out). Vanden (2008) studies a more sophisticated environment where the quality of information varies. He finds that option values are decreasing in information quality. If one interpreted the arrival of material inside information as increasing information quality, the effect may then play in a direction opposite to simple intuition. The complex relation between private information and option value motivate us to consider an additional measures of implied volatility, the implied volatility spread, which measures the average difference in implied volatilities between call and put options with the same strike price and expiration date. One would expect that an insider with positive news buys the call option and may sell the put option, increasing the value of the spread Consistent with intuition, Cremers and Weinbaum (2010) show that high values of the IV spread are associated with a positive abnormal performance of the underlying stock.

Next, we formally define the considered price-based option measures. In all cases, the weighting factor ω_j correspond to the the open-interest weight of option j.

Option Quoted Spreads Let t and i index trading dates and underlying stocks. 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

$$QS_{o,t}{=}\sum\nolimits_{j=1:J}\omega_j\left(\frac{a_{jt}-b_{jt}}{m_{jt}}\right),$$

where the quotes correspond to the end of the day values. We also consider a version that concentrates on highly levered (OTM) options (QS_{lo}).

Implied Volatility (*IVC* and *IVP*) For both calls and puts, the daily implied volatility is computed as an open-interest weighted average of OptionMetrics' implied volatilities ($OMIV$)

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

Implied Volatility Spread (*IVS*) Following Cremers and Weinbaum (2010), the IVS measure for a given underlying stock on a given day t is computed as

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

Only pairs with implied volatility and open interest records are included in the calculation. The intuition of this measure is as follows. Say good news are learned. A trader would then profit from buying calls or selling puts or doing both. In such cases, the implied volatility between calls and puts would move in opposite directions widening the value of their difference.

Volume-based Signals

Back (1993) introduces trading in a single at-the-money call option into a continuous-time version of Kyle (1985) with a single privately informed trader. He 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. These authors find that option volume has an informational role and can move stock prices. A limitation of the cited equilibrium option trading models 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 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.

Next, we formally define the considered volume-based option measures.[12]

Abnormal Volume in Options (AV) 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

$$AV_{o,t} = Volume_{o,t} - PredVolume_{o,t},$$

where total volume is the number of traded contracts on dat t. Predicted volume is computed using a linear regression model with total volume for the same underlying and the following contemporaneous controls: median volume in all equity options, VIX, the excess return of the value-weighted market portfolio, and the daily return of the underlying stock. [13]

Levered Volume Ratio (VR_{otm}) Based on Black's (1975) insight that informed traders value leverage, we compute the ratio of volume in OTM options to non-OTM volume. Specifically, for all options on the same underlying stock, we have

$$VR_{otm,t} = \frac{\text{OTM Volume}_t}{\text{(ITM+ATM) Volume}_t},$$

Naturally, if informed traders value leverage, a high VR_{otm} value may signal informed trading. In cases in which the denominator (but not the numerator) is equal to zero, we set the value of VR_{otm} to 100 (the 99% percentile of the empirical distribution).

[12] We do not compute PIN/AOI for options as OptionMetrics does not provide intraday trades. Easley et al. (1998), however, argue against the use of PIN in option markets.

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

2.3 Mixed-market Signals

Motivated by the theoretical literature discussed 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 (QSR) We study whether the informed trade effect in bid-ask spreads is proportionally larger in the option or stock market by computing the ratio $QSR_{o|s} = QS_o/QS_s$.

Volume Ratios Roll, Schwartz, and Subrahmanyam (2010) conjecture that private information may increase the value of option volume relative to the volume in the underlying. Thus, episodes of information-motivated trades can display higher values of their option/stock volume (O/S) measure.[14] Formally, the option stock volume ratio is given by

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

Option volume includes the total volume in 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 call and put options volume in the numerator, respectively. Of course, $VR_{c|s} + VR_{p|s} = VR_{o|s}$. We also consider a variation that is based on levered option volume

$$VR_{otm|s,t} = \frac{\text{OTM Option Volume}_t}{\text{Underlying Stock Volume}_t}.$$

Daily 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 so as to account for cross-market interactions. In particular, we propose a daily illiquidity SO measure which is defined as

$$DI_{s|o,t} = \frac{|Stock\ return_t|}{Option\ Volume_t},$$

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

where Option Volume accounts for day t volume in all options of the same underlying. We propose a second measure that, analogously, captures the interaction between stock volume and option returns. In particular, the daily illiquidity OS measure is defined as

$$DI_{o|s,t} = \frac{|Option\ return_t|}{Stock\ Volume_t},$$

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

2.4 Data and Implementation Details

Data Stock-based measures at high and low frequencies are computed using monthly TAQ and CRSP, respectively. For each stock, we compute the intra-day NBBO prices using the interpolated time method in Holden et al. (2014). We obtain option data from the Ivy OptionMetrics database, which provides end-of-day information for all exchanged-listed stocks on U.S. stocks, including option prices, volume, and implied volatility.

Intraday Averages In addition to dollar weighted averages, we also computed intraday stock-based measures using the number of shares as weights, obtaining similar results.

Trade Direction We consider three trade-typing conventions to determine wether a given trade is sell- or buy-initiated and the value $d_i \in \{-1, +1\}$ According to the Lee and Ready algorithm (1991, LR), a trade is a "buy" when $p_i > m_i$ and a "sell" when $p_i < m_i$. According to the Ellis, Michaely, and O'Hara (2000, EMO) algorithm, a trade is a buy when $p_i = a_i$ and a sell when $p_i = b_i$. According to the Chakrabarty et al. (2007, CLNV) algorithm, a trade is a buy when $p_i \in [0.3b_i + 0.7a_i, a_i]$ and a sell when $p_i \in [b_i, 0.7b_i + 0.3a_i]$. In all three cases, if the trade direction cannot be assigned, the tick test is used: A trade is a buy (sell) if the most recent prior trade at a different price was at a price lower (higher) than p_i. For brevity, we report results for the Lee-Ready algorithm only. Our results are similar for the other two specifications.

3 Insider Trading Sample

3.1 Background on Insider Trading

Insider trading is a term that includes 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. According to the SEC, on the other hand, illegal insider trading (IIT) 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 he trades on material, nonpublic information about a firm to which he 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. Over the last decades, largely due to a number of important U.S. Supreme Court decisions, the scope of what constitutes IIT has increased. For example, the 1983 Supreme Court decision in Dirks v. SEC expanded the definition of insider to include "constructive insiders" such as underwriters, accountants, and lawyers who, once hired, have legal duties to keep material information disclosed by the firm as confidential. During our sample period, IIT may also include "tipping" such information, securities trading by the person "tipped" or by those who misappropriate such information. The definition of an insider was also broadened by the SEC's Rule 14e-3 (1980) which explicitly prohibits trading based on nonpublic information about impending tender offers, even if the trader owes no fiduciary duty to the target firm.

The existence of alternative interpretations over what constitutes illegal insider trading activity continues to this day. In this paper, we do not seek to settle the debate. In fact, it is not important for us whether a given trade is technically illegal or not. Rather, our identification strategy relies on two conditions (i) the considered trade was motivated by actual information, as opposed to, say, sentiment, and (ii) that material information was not widely available to market participants at the time of the trade. This approach allows us to concentrate on all investigations where the SEC reported that conditions (i) and (ii) are met, regardless of the legal resolution of the case.

3.2 Data Collection

We retrieve the list of SEC investigations from all SEC press releases that contain the text "insider trading." We use this list to obtain all the available civil complaint files available on the SEC website.[15] In cases in which the complaint file is not available at the SEC website, we rely on manual web searches and on information from the U.S. District Court where the cases was filed. We collect all files 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 data points.

The resulting sample of 453 documents 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 in tables by hand. Available information typically includes biographical records of defendants, individual trades, a description of the leak that the trades are linked to, as well as 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 the contract characteristics for options. Whenever only a date range is available, we only consider as trading dates the first and last day of the range. This condition reduces the potential number of trading dates but yields well-identified trading date records throughout the analysis. We also record individual names in cases in which more than one person/firm executed trades 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 purposes, the key information event records include the companies involved, the nature of the leaked information (e.g., a new product), and the date at which the information is 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.

[15] We collected online all the files in 2013. At the time of collection, the oldest available complaint file was for the year 2001.

3.3 Descriptive Statistics

Our data collection procedure yields 453 legal cases. Table **??** shows the distribution of cases by type (Panel A), year (Panel B), and the number of firms involved (Panel C). The most frequent event type is mergers and acquisitions (55.90%) followed by earnings announcements (15.06%). The categories Business Events and Corporate Events (10.71%) include, among others, items such as information about products, firm's projects, patents, FDA medical trials, corporate restructuring, bankruptcy, and fraud. The average number of cases per year in the sample is 30.83, with the maximum of cases (46) filed in 2012. This number has been growing steadily over time and partially recognizes the increased SEC efforts to track illegal insider trading (e.g., Del Guercio et al. (2013)). 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 present the properties of our sample at the level of each trade, which is our main unit of observation. We identify a total of unique 5,058 trades in our sample. In Panel A, we show the distribution of trades with respect to the instrument that is used to trade. The vast majority of trades are executed via stocks (67.06%) and options (31.83%). The remaining few cases are trades in ADS and bonds. In Panel B, we show the breakdown of trades with regard to the trade direction. We identify 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 places earlier on. Consequently, our sample of trades spans a longer time period of 1995–2015. The sample is distributed quite uniformly over time with over 100 trades in each year between 1999 and 2014. We observe a relatively small number of trades in the 1990s and then towards 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 SEC. The observed dispersion of trades across years is an attractive feature of our data that allows us to deal with common identification issues, such as time-specific macro events, etc.

In Panel D, we consider the distribution of trades with respect to the primary industry classification of a traded company. Our definition of industry is 2-digit SIC code. The distribution of trades is highly dispersed across many different industries. The top 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 properties of trades and trading parties. We find that the median time between the arrival and the use of information by insiders is 2 days. In turn, the median number of days from trade till information event is 7 days. The majority of cases involve single trades in a given company and news, but a subset of traders execute more than one trade. The median horizon between the first and the last such trade is 8 days. Further, a median trader in our sample executes 10 trades with the maximum of 97 trades. A median firm receives 16 trades and a median legal case involves 2 firms. A median age of tippers and traders is almost identical and equal to 45 years. The vast majority of tippers and traders in our sample are male. The profits reported by traders are highly skewed with the average trade profit of $1,014,000 and the median of $90,000. 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 the used information. Naturally, an interesting issue is: 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 opening of the day of the first informed trade to the opening price immediately after the information becomes public. For example, if information about an earnings announcement is disclosed overnight on date t, we consider the opening price on date $t + 1$. Table IV displays 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 greater than 33.5%. These values are remarkable given than the median time interval from a trade to the private information disclosure is seven days. In fact, one could treat these numbers as a lower bound on the true signal strength since about 30% of trades are in options, that is, leveraged trades. To put these numbers in another perspective, we construct benchmark returns for the sample of 13D filers between 1994 and 2014. The benchmark return is based on the return measured from the open of the day when the 13D filer trades an asset until the open 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 et al. (2013); Collin-Dufresne and Fos (2015)). The mean and median returns for 13D filers are 4.9% and 2.4%, respectively.

4 Evidence from Illegal Insider Trading

4.1 Empirical Design

Our analysis utilizes a setting of insider trading in which we can observe the use of private information for a given company on a given day. We hypothesize that if firm-specific measures of information capture the presence of private information, they should show abnormal behavior on days when such information is used. The implicit assumption of this design is that on any other days the likelihood of the use of private information is less than one. Given that private information is unlikely to be used on every single trading day we believe this assumption is not very restrictive.

Our empirical methodology is a simple event study analysis with events being defined by insider trades. The methodology requires that we specify a representative window of data that would allow us to track the behavior of information measures for a given company prior to (pre-event window) and on the event day. We set the length of the pre-event window to 15 trading days. For each firm that is being traded by insiders, we compare the value of information measure on the event day and the average calculated over the pre-event window. The assumption is that the observations in the pre-event window represent a normal market behavior, distinct from what happens on the event day. A standard approach would be to select the trading days that just precede the insider trading day. However, information measures may be serially correlated or some unrecorded informed trades may take place right before the event date. Both situations would have lowered the statistical significance of our results since the average in the pre-event window would be magnified by these observations. In addition, to the extent that the insider trade takes place on the information event day or just before, it is possible that other traders might speculate on the direction of the news right before the event or they can internalize their decision to trade based on their assessed probability of informed trading (e.g., Chae (2005)). For example, many traders bet on the direction of earnings announcements right before these are released. Such trades would bias our results in two ways: upwards if the other trades happen on the insider trading dates, downwards if they happen before the insider trades.

To illustrate the consequences of the different modeling choices, we plot our measures in the event window, along with the two standard errors bounds around the mean. The untabulated results indicate that some measures indeed get elevated prior to event date, which might bias downward the magnitude of our results. To address this bias, we consider an alternative experiment in which we shift the pre-event window to the period of 21-35 trading days before the event date. Skipping the last 20 days in the pre-event window is likely to eliminate any serial correlation or abnormality around the event date. Further, we eliminate all the cases in which the insider trades happen less than 4 days prior to the corporate event to which they are matched. This restriction makes it more plausible that any trade prior to or on the event date is not a pure speculation on the direction of the event.[16] We show the construction of the event window in the figure below.

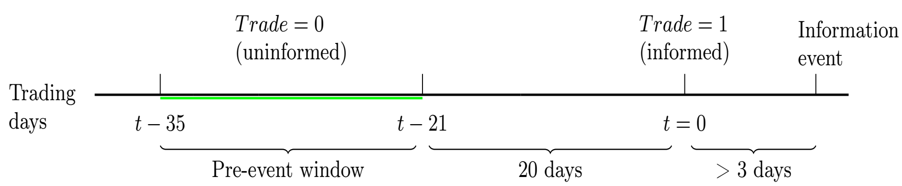

Figure 1. Event Study Time Line

To evaluate the quality of the alternative event window specification, we plot the same set of figures as before, except that now we use the extended window and skip the short horizon cases. The results suggest that the restrictions put on the model filter the insider shocks more precisely. We observe that the observations in the pre-event window are much more stable and do not exhibit almost any serial correlation or time trend. The rest of our empirical tests will consider this design as our benchmark.

In our first test, we consider all insider trading events and compare the values of information measures for companies involved in such trades within the event window. We estimate the following multivariate regression model:

$$IM_{it} = a + b\times TRADE_i + c\times Controls_{it} + \mathrm{d}_i + \mathrm{e}_t + \epsilon_{it}. \tag{1}$$

[16] In our data, a trader (or a group of traders) may trade a given company more than once on a given day either because they split their trades or because they use different instruments to trade. To avoid double counting, we include only one daily observation and the corresponding pre-event window. Further, some traders trade the same company in 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 dimension.

where $IM_{i,t}$ is the information measure for company i measured at time t. Throughout all models, we winsorize IM measures at the 1% level. $TRADE_i$ is an indicator variable equal to one on the day in which a company is traded by insiders and zero on each trading day of 35 to 21 trading days before. $Controls$ is a vector of firm-specific controls, including $LNSIZE$, $LNVOL$, $TURNOVER$, and equity price per share (PRC). To account for the possibility that information measures and controls might vary generically over time and across firms, in most regression models we also include firm-fixed and time-fixed effects. The coefficient of interest in the following regression is b.

The identifying assumption of the above model is that any time-series variation in information measure around insider trading days is unlikely to be correlated with any other observable than the trading itself. However, this assumption generally need not be true, in which case our results could be subject to omitted variable bias.[17] One of the main advantages of our setting is that we can actually ensure the bias is not a first-order concern. The most important feature of our setting that makes the identification strong is based on the fact that the arrival of information is unlikely correlated with any observable correlated with information measures because the insider tips are exogenous shocks resulting from personal relationships in the information network. In fact, the data in Panel E of Table III show that the distribution of trades across months is quite symmetric, which makes it unlikely that our trades are clustered in information sensitive months. What we also observe, and document in Section **??**, is that the relationship between insider trades and information measures does not depend on the distance between information arrival and information use. In general, the median value of that distance is a mere one day.

To further buttress our identification strategy, we take advantage of the panel structure of our data. The first feature of our experiment to note is that 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. Second, we focus on a narrow event window, which insulates us from any longer-term trends driving the data.

In our formal test, we compare each firm that is involved in insider trading (treatment group) to a matched portfolio of firms (control group) with similar characteristics. Next, we make cross-

[17] In our analysis, we face one more empirical challenge which is related to our sample selection. We discuss our empirical strategy addressing this issue in Section 4.3.

sectional and time-series comparisons using a standard difference-in-differences estimation technique. Our control portfolio is composed of firms that belong to the same 2-digit SIC industry and the same market capitalization quintile. Subsequently, we calculate the arithmetic average of a given information measure in the portfolio and subtract this average from the information measure, which results in a controls-adjusted information measure ($CAIM$). 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 (1) except that we replace IM with $CAIM$.

$$CAIM_{it} = a + b\times \mathrm{TRADE}_{it,t-k} + c\times \mathrm{Controls}_{it} + \mathrm{d}_i + \mathrm{e}_t + \epsilon_{it}. \quad (2)$$

4.2 Baseline Results

In Table V, we present the results from estimating the regression model for stock-based measures of information. In Panel A, we estimate the simple model with $TRADE$ and basic controls. Of the seven measures we consider, six are statistically significantly different on event days, all at least at the 5%level of statistical significance. Notably, the coefficient of DI is negative, which suggests that liquidity is generally higher on the informed trading day. In Panel B, we additionally introduce firm-fixed effects to account for the possibility that information measures and firm characteristics might vary across firms thus rendering any comparisons difficult. Using this specification makes the measure of $Lambda$ insignificant and the coefficient of AOI stays borderline significant. All other effects remain statistically strong. In Panel C, we further include time-fixed effects to account for the possibility that the measures are time varying. We find that the coefficients of QS, PR, RV, and DI retain their economic and statistical significance. In general, the difference in magnitudes between Panels B and C is not large, which suggests that the time series is not the main source of variation in the data. Finally, in Panel D we replace IM in Panel C with control-adjusted information measures, $CAIM$. This most comprehensive empirical test leaves only two coefficients, those of PR and DI, significant both significant at the 1% level. The magnitudes of the two coefficients do not vary across the two panels which suggests that our treatment effect might be fairly independent of other firm-specific and time-specific observables.

Next, we estimate a similar set of regression models for option-based information measures. Panels A-D of Table VI present the results. Contrary to the weak evidence for stock-based measures, we find that option-based measures display significant abnormal behavior on the event days in the most comprehensive control-adjusted tests. In particular, we find that six out of seven measures have significant coefficients of $TRADE$. The most robust measures are IV_c and IV_p, which are consistent with the underlying theories. In turn, while the bid–ask spread for OTM options and illiquidity are also statistically significant, both retain coefficients that are negative. In fact, the feature that liquidity is higher on days of insider trading is consistent with the results we obtain for stock-based measure of liquidity.

Finally, we estimate the regression models for mixed measures and report the results in Table VII (Panels A-D). We observe the most consistent patterns for measures that rely on the mix of options and stock volume: $VR_{o|s}$, $VR_{c|s}$, $VR_{p|s}$, and VR_{otm}. They are all 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 returns.

Overall, our results indicate that option-based and mixed measures are better measures to pick up instances of informed trading in the data. In turn, the widely used stock-based measures do not seem to correlate significantly with periods of insider trading. We also conclude that incorporating volume from both option and underlying asset markets in the information measure improves its performance. Finally, throughout all markets we find a negative correlation between informed trading and measures of illiquidity, a result that is generally consistent with the strategic liquidity timing effect, previously documented by Collin-Dufresne and Fos (2015).

4.3 Sample Selection Bias

One could argue that in its decision to launch an investigation, the SEC may screen trades based on the measures we find informative. One would then be concerned about sample selection bias. This concern would be specially troublesome if insider traders get exposed *only* when these measures display abnormal values. If that was the case, one could then overestimate the information measures' capacity to detect information. Our analysis does not support this view. First, almost all stock-based measures fail to reveal private information. Thus, it seems unlikely that the SEC would screen on such measures since they do not display abnormal behavior on the insider trading days. Second, the most robust stock-based measure, daily illiquidity, moves in the opposite direction to what informed trading would have predicted. That is, it displays lower values when there is insider trading. One would then need to believe that the SEC is particularly sensitive to criminal activity when markets look orderly and abnormally liquid. Third, prior evidence suggests that a significant fraction of investigations originate by external tips. Meulbroek (1992) studies a sample of cases filed by the SEC in the eighties 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 like 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 the 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.

Formally, we conduct three independent tests–the SEC Whistleblower Program, case complexity, and signal strength– to assess the existence of selection bias.

Evidence from the SEC Whistleblower Program The first and arguably the most convincing form 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 provision of *original information* directly to the SEC or related agencies. Importantly, the program defines original information as that (1) derived from the independent knowledge or analysis of a whistleblower, (2) not known to the Commission from any other sources, (3) not exclusively derived from an allegation made in a judicial or administrative hearing, in a 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 measures.

Since the Program was implemented in 2011, we limit our analysis to cases that were filed during the period of 2011-2015. Our sample includes 166 different cases, 37 of which were investigated through the Program and 129 which do not have a precise source of investigation (could be result of SEC analyses or based on independent tips). In Table VIII, 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 Whistleblower 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 measures to detect private information depends on the source of investigation. To this end, we estimate a modified version of the regression model in equation (2).

$$
\begin{aligned}
CAIM_{it} = a + b \times \mathrm{TRADE}_{it,t-k} + c \times WB_{it,t-k} + d \times \mathrm{TRADE}_{it,t-k} \times \mathrm{WB}_{it,t-k} \\
+ e \times Controls_{it} + f_i + g_t + \epsilon_{it}. \qquad (3)
\end{aligned}
$$

WB is an indicator variable equal to one if a trade is part of the 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 IX. Panel A shows the results for stock-based measures. We find no statistically significant difference for six out of seven measures. The only statistical difference is the positive coefficient of the interaction term for *DI*, 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 measure would be picked up by the SEC as suspicious. In Panel B, we report no significant difference for all option-based measures. Finally, Panel C indicates a significant result only for one mixed measure (*VR* for puts).

Altogether, our results suggest that the selection based on abnormal variation in information measures is unlikely to explain our results. Moreover, assuming that pre-2011 cases underlies similar selection process we can argue that the selection concern is unlikely to explain all the cases we study.

Evidence from the case complexity Another identification idea we pursue is based on the nature of cases we analyze and is similar in spirit to that used in Meulbroek (1992). Specifically, some cases investigated by the SEC are quite simple as they involve only one or two unique companies, but some are much more complex and involve up to 25 different companies. It is reasonable that the probability that the SEC picks a particular case based on the variation in information measures is greater for simple cases than it is for complex cases. Intuitively, for a generic case involving, say, ten firms, it is unlikely that detection occurred based on independent publicly observed price or volume movements in *each* stock. Rather, even when the investigation originated in screening IMs, it is likely that trades in subsequent firms were unravelled as part of an ongoing investigation involving access to brokerage accounts, etc. Consequently, if the selection bias drives our results, one should expect the informativeness of measures to be greater for simple cases than for complex cases. We define a simple case as one with at most two different companies involved and a complex case as one with more than two companies. Next, we estimate the following regression model for the entire sample of cases.

$$
\begin{aligned}
CAIM_{it} = a + b{\times}\mathrm{TRADE}_{it,t-k} {+} c \times SIMPLE_{it,t-k} + d{\times}\mathrm{TRADE}_{it,t-k}{\times}\mathrm{SIMPLE}_{it,t-k} \\
+ e \times Controls_{it} + f_i + g_t + \epsilon_{it}, \qquad (4)
\end{aligned}
$$

where *SIMPLE* is an indicator variable equal 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 a differential behavior of measures for trades obtained from simple cases relative to those obtained from complex cases. The results are reported in Table X. We find no significant difference in the impact of informed trading across all information measures. The only exception is the negative coefficient for realized volatility. Hence, we can conclude that the ease with which the SEC could potentially identify informed trading does not affect the informativeness of our information measures.

Evidence from the Informed Trade Incidence. In our third test we split the sample into two groups based on whether the quantity traded by the informed individual is high or low. Specifically, we identify, day-by-day, trades that are below and above the median of the empirical distribution of the informed trade volume to total volume ratio. The intuition of this test is that the probability of detection and the probability of selection bias are higher when the informed investor trades a high proportion of the day volume of a given security. The results work against this null hypothesis: Information measures are slightly less informative for high informed volume cases.

A different possibility is that, in anticipation of a potential investigation, informed traders alter their trading behavior with consequences for the dynamics of prices and volume. We view this hypothesis as more plausible. One such example would be given by informed traders strategically waiting for high volume to trade. Although our evidence suggests that the quality of information measures is the same irrespective of when the informed trade, we cannot rule out this hypothesis entirely. To extend this analysis, we investigate the time series of firm-level volume within the event window controlling for firm-fixed and time-fixed effects. The results are presented in Figure 2. We find that volume does not show an abnormal behavior on days associated with insider trading activity. Of course, our paper cannot address the issue of how useful public information would be with counterfactual regulations.

4.4 Additional Tests

In this section, we present a number of additional tests that help us evaluate the quality of information detection in various conditioning settings.

The cross-section of options In trading on private information using options, investors have the ability to choose options with different maturities and different leverage. From the cost-benefit tradeoff it would make sense to exploit more leveraged (OTM) contracts as they provide a higher gain 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 falls after the information is publicly revealed. Long-term options are likely more expensive and less liquid. We tests these predictions by conditioning the aggregate VR measures on both maturities and moneyness. At-the-money options (ATM) are defined as those with moneyness greater than 0.97 and less than 1.03. Any options with values outside of this range are classified as either in-the-money (ITM) or out-of-the-money (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 (1) and in (2) for the selected cross sections. The results are presented in Table XII.

In Panel A, we present the results from the baseline regression, including firm-fixed and time-fixed effects. Consistent with our prior, we find that the economic significance of the informed trading 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. Similar effect can be observed for the ultra-short options. In Panel B, we further adjust information measures using the industry and size peers as a benchmark. The results are qualitative identical and quantitative not far from 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.

Conditioning on insider trading intensity One question arising from our study is how important the trades of insiders are relative to the overall trading volume in the market. To the extent that such trades are small it might not be surprising that their activity might not be picked up in the data. We investigate this question in two ways. First, we provide summary statistics on the share of insider trades as a fraction of total stock and option (calls and puts) volume. The shares are calculated using the aggregated volume of insider trading for a given company, asset type, and trading day. We present the results in Table XIII.

We observe that option trades constitute a larger fraction of overall trading volume. On average, both call and put trading make up more than 30% of the total trading volume. The same quantity for stocks exceeds 10%. We believe all these quantities are economically large and underlie the importance of insider trading. At the same time, the cross-sectional distribution of the share is also quite large and skewed to the left, as indicated by large values of standard deviation and smaller median values. One could then ask whether smaller trades actually dampen the economic significance of our results. In this regard, we now estimate whether a larger share of insider trading have more impact on asset prices and thus is more indicative of information-driven trades. To test this hypothesis, we split both stock and option trades into low (high)-intensity trades if the respective insider trades are below (above) the within-asset median. We then estimate the regression model in (2) for all information measures conditional on low and high-intensity trades. We present the results in Table XIV.

In Panels A and B, we present the results for stock-based measures. We observe that the results for high-intensity sample qualitatively reflect our prior results for the unconditional sample: the only two statistically significant measures are PR and DI. Interestingly, DI becomes insignificant when the share of insider trading is low. This result is consistent with the view that large trades might search more carefully for periods with overall low market illiquidity. Further, QS and $Lambda$ become statistically significant in times of low informed trading intensity. However, the magnitudes of the relationships are negative, thus inconsistent with the underlying theories of trading. Finally, the measure of price impact does not seem to be significantly to informed trading even in periods of high intensity. In Panels C and D, we consider option-based measures. The high-intensity trades now are less related to informed trading than were unconditional trades. This could be partly a reflection of the smaller sample size. The two statistically significant measures remain IV_c and DI_o. In general, most measures are slightly larger economically, but not so different qualitatively. We obtain similar results for mixed measures, in Panels E and F. Again, the sample of high-intensity trades is very similar qualitatively to the unconditional sample and the magnitudes of coefficients are slightly larger than those for low-intensity trades.

Overall, we conclude that the qualitative results from high-intensity trades are not very different from those for unconditional sample, which supports our earlier interpretations. Further, while in most cases the economic magnitudes of the coefficients of $TRADE$ go up—consistent with the view that larger insider trading share has a greater impact on the informativeness of signals—the qualitative differences across the two subsamples are not as stark.

Conditioning on insider sophistication A unique aspect of our data is the ability to identify individual traders. Some of the insider traders are professional investors or corporate executives while others are individuals with no direct connection to the finance sector and possibly less sophisticated trading behavior. The implication of such heterogeneity is that sophisticated investors might submit larger orders and participate in information-sensitive option markets and thus they might be detected more by measures of informed trading. At the same time, they might be more strategic in their trading behavior and thus their actions might be more difficult to detect. In this section, we investigate these two possibilities formally. We define sophisticated investors as those with finance jobs (e.g., traders, brokers, CFOs) or those who hold top executive positions (e.g., CEOs, COOs, or board members). On average, the sophisticated traders constitute about 51% of all traders.

We estimate the regression model in (2) for all information measures separately for unsophisticated and sophisticated traders. We present the results in Table XV. In Panels A and B, we present the results for stock-based measures. The qualitative results look very similar across two samples of traders except that RV and QS become statistically significant for the sample of unsophisticated traders. In Panels C and D, we present the results for option-based measures. In general, we observe that the coefficient of $TRADE$ becomes smaller in magnitude and less significant for the sample of sophisticated trades, consistent with the predictions that such trades are better disguised from the public. Similar conclusions can be drawn from Panels E and F for mixed measures. Throughout all measures, we also find that the negative relationship between $TRADE$ and illiquidity measures is stronger for sophisticated trades, which supports the interpretation that such traders are more strategic in their behavior.

Conditioning on corporate event types The information used by insider traders relates to three categories of corporate events: mergers and acquisitions, earnings announcements, and general corporate events related to product release or strategic investment plans. In this section, we examine whether the quality of information measures depends on a particular event category. In particular, we will distinguish between schedule events such as earnings announcements and unscheduled events such as mergers and acquisitions. This distinction is relevant because it can inform us whether alternative explanations can be behind our results. In particular, empirical tests for earnings announcements can also fit the model with differences of opinions while the tests for mergers are more information-only events. To this end, we estimate the regression model in (2) for stock-based, option-based, and mixed information measures as dependent variables separately for mergers and earnings events. The results are presented in Table XVI.

In Panels A and B, we present the results for stock-based measures. We observe that the unconditional evidence we observed before is largely mirrored by the results for the sample of mergers: PR is positively related while DI is negatively related to $TRADE$. At the same time, there is no significant effect observed for the sample of earnings. In Panels C and D, we present the results for option-based measures. Again, the results are significantly stronger for the sample of mergers while only one measure, DI_O, is statistically negatively related to $TRADE$ in the sample of earnings. Finally, in Panels E and F, we report the results for mixed measures. We find that mixed measures are good indicators of informed trading for both subsamples of trades.

Overall, we find that the mixed measures are the most robust predictors of informed trading for two major types of corporate events. Further, the sample of mergers generally displays more robust relation to informed trading events than does the sample of earnings announcements. Given that mergers and acquisitions are more difficult to time by regular traders since they are not pre-scheduled, one could argue that our results are unlikely to merely reflect non-insider investors' response to pre-announced corporate events.

Conditioning on the direction of information In our next test, we examine whether the quality of information measures relates to the sentiment of the information. More than 80% of all insider trades are about positive news while slightly less than 20% are about negative news. We estimate the regression models for the two types of news for the model in (2). We report the results in Table XVII for stock-based measures (Panels A and B), option-based measures (Panels C and D), and mixed measures (Panels E and F).

Our findings indicate that measures of information are generally better able to pick informed trading when the trade is placed in anticipation of a positive news. For stock-based measures both PR and DI are statistically significant. Similarly, six out of seven measures are statistically significant for option-based measures. Finally, five out six mixed measures are statistically significant. The coefficients become significantly weaker for the sample of negative news. Only PR is statistically significant among stock-based measures. In the sample of option-based measures all coefficients are statistically insignificant. However, three VR measures are also statistically significant for negative news, which further confirms the robustness of these measures.

Further evidence on volume ratios One of the best performing measures in our tests are volume ratios (VR). In this section, we ask two additional questions that shed more light on the performance of the measures. First, we examine to what extent the informed trading predictability of the measure depends on the volume of the insiders themselves. As we have shown before insiders, especially in option markets, tend to make up a significant portion of the total volume. Hence, the abnormal behavior of VR could be a mechanical reflection of the fact. In Table XVIII, we reestimate the VR measures excluding the volume coming from insiders, coming either from option or stock trades. While the economic significance of the results gets smaller, the statistical relationship with the informed trading days remains intact. Thus, one can argue that the variability of the VR is not a mechanical reflection of the insiders. Of course, the remaining abnormal option volume could still be a consequence of the insiders' trades. In this sense, the logic of our test here is a partial equilibrium one.

In a second test, we examine the behavior of VR around the insider trading and public announcement dates. To this end we plot the cross-sectional average of VR measures (for aggregate, call, put, and levered option volume) for the window of 35 to 21 days prior to insider trading, for the insider trading date 0, and for 1 to 15 days following the public announcement of the news on which insiders trade. Each measure is netted out of the firm-fixed 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 **??**. Consistent with our earlier results we observe that each of the four measures spikes at date 0. In addition, we also observe that the measures revert back to their normal levels following public news release, a pattern consistent with informed trading taking place prior to the public news release.

Other tests

Size sorts Insider traders in our sample execute trades in a large cross-section of companies with different market capitalizations, trading, 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 (2) for the subsample of firms with the market capitalization below and above the median value in the sample. Our untabulated results reveal two facts. First, we do not find significant differences in the effect of $TRADE$ on various information measures, which provides robustness to our earlier findings. Second, we find that the conclusions for illiquidity measures are strongly related to equity size. The negative relationship with $TRADE$

is particularly strong for the subset of companies with below median market capitalization. This result is consistent wth the view that informed traders with strategic liquidity timing are likely to engage in such activity for firms which are more affected by such illiquidity costs.

Signed options volume One of the limitations of such measures is that they do not recognize whether the volume in the market is originated by the buy or the sell side and whether the trade opens a new position or closes an existing one. This distinction makes sense from the perspective of the insider trading which by design is one sided. With this motivation, we used data from the International Securities Exchange (ISE) Open/Close Trade Profile to recreate the VR measures. The compromise is that ISE data are available for the sub-period 2005-2012 and, in contrast with OptionMetrics, they represent 30% of the total volume in individual equity names. Unreported results (available upon request) indicate that the best power to detect informed trades have the measures based on call volume and originated on the buy side. This result might not be too surprising if one factors in the fact that the majority of our insider trades are taking a long position in the asset in anticipation of the positive news and long call contracts are the easiest way to implement such trade. Further, the measures which capture informed trading better are those for which volume relates to newly opened positions, a result that corroborates the evidence in Ge et al. (2015).

5 Concluding Remarks

Information asymmetry in financial markets is ubiquitous and it affects the behavior of asset prices as well as corporate decisions. Academic research to date has taken several attempts to identify informed trading based on publicly observed data, but this effort is empirically challenged by dealing with 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 so as to evaluate such signals against actual trades based on private information.

Our research sheds new light on how the traditional measures of informed trading perform and offers new insights for future investigations. First, we show that highly popular stock-based measures are relatively noisy and do not exhibit strong correlation with instances of real informed trading. In turn, option-based measures, which have been less studied in the literature, are desirable in this regard. Remarkably, some of the most robust measures are based on a mix of signals from both equity and derivative markets. Second, we show that the signal contained in volume, and in the ratio of option to stock volume in particular, is generally useful to predict 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 in volume. This need seems to be increasingly important in more recent years given the disruption of high-frequency trading (e.g., Chordia et al. (2013); O'Hara (2015)). A structural PIN-like model that exploits volume, such as that in 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 some novel evidence on the underlying mechanisms of information transmission. In particular, the negative correlation between informed trading and liquidity-based measures that has been highlighted in a recent paper by Collin-Dufresne and Fos (2015) need not be solely associated with strategic incentives to time trades so as to reduce illiquidity costs (Collin-Dufresne and Fos (2016)). For traders with information of significant value, like the average trader in our sample, or that fear competition from other informed traders, illiquidity costs may appear as relatively small. Further, detailed evidence from the cross-section of traders, assets, and their trades corroborates the information-based explanation of our findings.

Our results suggest that more 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 what combination of signals 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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Appendix: List of Information Measures

The complete specification of each considered measure is provided in Section 2.

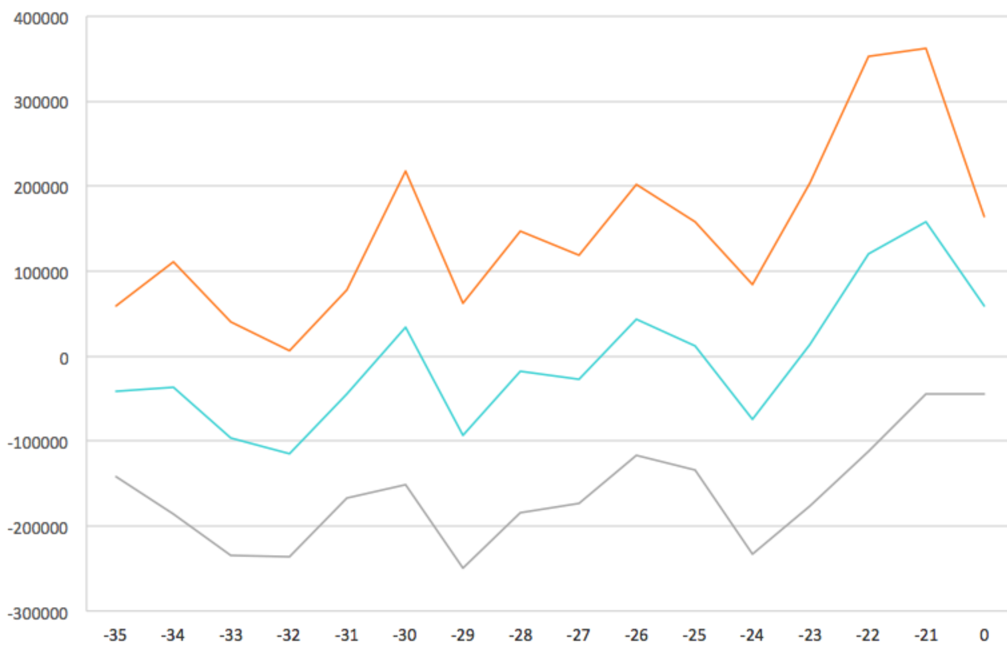
Stock-based Measures (TAQ and CRSP)

- QS: Quoted bid–ask spread for stocks (TAQ NBBO) as a percent of the midquote. Time weighted daily average.
- PI: Price impact for stocks (NBBO). Five-minutes midquote change. Dollar-weighted daily average. Lee-Ready trade sign classification.
- PR: Price range, defined as the maximum daily ask price minus the minimum bid price (from CRSP), as a percent of the average value.
- RV: Daily realized variance based on 30-minutes intervals.
- Lambda: Kyle's lambda. Slope of a regression of 30-minute intra-day returns on signed volume.
- DI: Daily illiquidity, defined as the ratio between daily absolute stock returns and volume.
- AOI: Absolute order imbalance. Absolute value of daily the ratio of (number of buys-number of sells) to the number of trades. Lee-Ready trade sign classification.

Option-based Measures (OptionMetrics) The following are the baseline option-based measures from OptionMetrics data. OMIV denotes OptionMetrics' implied volatility.

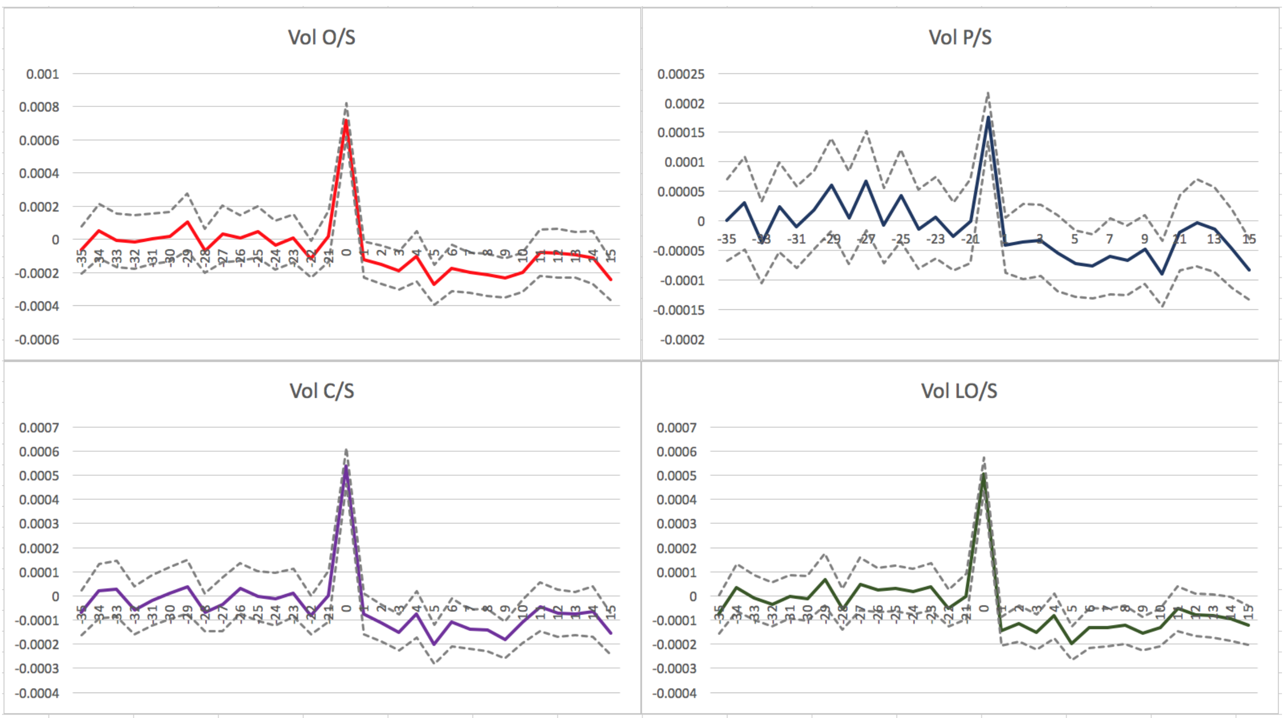
- QS_o: Daily arithmetic average of quoted bid–ask spread for all traded options on the same underlying.
- IV_o: Daily arithmetic average of OMIV for all traded options on the same underlying.
- IVS: Implied volatility spread, given by the average difference in OMIV between call and put options with the same strike price and expiration date. Open–interest-weighted average.
- VR_{otm}. Levered option volume, given by the ratio OTM/(ATM+ITM) option volume for all traded options on the same underlying
- $VR_{o|s}$. Total option volume/Stock volume.
- $VR_{c|s}$: Total call volume/Stock volume.
- $VR_{p|s}$: Total put volume/Stock volume.
- VR_{los}: Total OTM option volume/Stock volume.

Figure 2. Insider Trading Effect on Trading Volume



Note: The figure presents the average values (aggregated across all trades) of volume, along with their 2-standard error bounds, within the event window of trading days for firms involved in insider trading. 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. Time 0 denotes the time of insider trade.

Figure 3. Option/Stock Volume Ratios



Note: The figure presents the average values (aggregated across all trades) of volume ratios, along with their 2-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 announcement of the public 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.

Table II
Descriptive Statistics: Information Measures and Regression Controls

Panel A reports the mean, median, and standard deviation calculated across time and firms of stock-based information measures 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. $LNSIZE$ is the natural logarithm of the market value of equity, $LNVOL$ is the natural logarithm of the stock trading volume, $TURNOVER$ is the stock turnover defined as the ratio of daily volume and number of shares outstanding, PRC is the stock price. All measures have been winsorized at the 1% level. Information measures in Panels A, B, and C are defined in Section 2. All information measures, $TURN$OVER, and PRC have been winsorized at the 1% level.

Variable	mean	median	st.dev.
Panel A: Stock-based measures			
QS_s*100	0.56	0.20	0.89
PI_s*100	10.93	4.69	18.21
PR_s	4.86	3.67	3.99
RV_s	0.11	0.05	0.15
AOI_s	0.15	0.11	0.15
$Lambda_s$	0.15	0.02	0.33
DI_s	0.60	0.04	2.98
Panel B: Option-based measures			
QS_o	0.58	0.48	0.37
QS_{otm}	0.85	0.75	0.48
IV_c	0.55	0.48	0.26
IV_p	0.59	0.51	0.27
IVS	-0.01	-0.01	0.05
AV_o	241.33	-33.29	9636.49
VR_{otm}	29.28	2.28	43.45
DI_o*100	0.15	0.00	0.66
Panel C: Mixed measures			
$QSR_{o\|s}$	674.76	391.47	854.13
$VR_{o\|s}$*100	0.13	0.05	0.22
$VR_{c\|s}$*100	0.09	0.03	0.15
$VR_{p\|s}$*100	0.05	0.01	0.10
$DI_{s\|o}$*1000	0.47	0.03	1.85
$DI_{o\|s}$*1000000	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
Descriptive Statistics: Trade Characteristics

The unit of observation is the insider trade. **In Panel A**, we classify trades by the trading instrument. **In Panel B**, we classify trades by the direction of trading. **In Panel C**, we show the distribution of trades by year. **In Panel D**, we show the distribution of insider trades with respect to the traded company's primary 2-digit SIC code. **In Panel E**, we report 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)

Descriptive Statistics: Trade Characteristics (continued)

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 open price on the day following the public disclosure date. Returns are split according to positive and negative news. Aggregate return takes a negative news return with the negative sign. Returns for 13D filers are measured from the open price of the day 13D filers trade until 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
Stock-based Measures: Baseline Specification

The dependent variables are stock-based information measures, measured at the company level at time t over the period 1995-2015. *TRADE* is an indicator variable equal to one for days of insider trading activity and zero for trading window of 35 to 21 days prior to the event day. 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** includes firm fixed effects. **Panel C** additionally includes time fixed effects. **In Panel D**, we additionally adjust measures of information subtracting average values of the portfolio of matched firms. The matching is performed along 2-digit SIC industry code and the same market capitalization quintile. Standard errors (in parentheses) are clustered at the firm dimension. ***, **, * denote 1%, 5%, and 10% level of statistical significance, respectively.

Signal		Price			Volume	Both	
	QS_s	PI_s	PR_s	RV_s	AOI_s	$Lambda_s$	DI_s
Panel A: Baseline estimates							
TRADE	-0.134***	-0.620	0.543***	0.015**	-0.015***	-0.037***	-0.352***
	(0.029)	(0.535)	(0.149)	(0.006)	(0.005)	(0.010)	(0.083)
LNSIZE	-0.211***	-3.263***	-1.012***	-0.032***	-0.019***	-0.127***	0.162
	(0.052)	(0.638)	(0.210)	(0.011)	(0.006)	(0.017)	(0.133)
LNVOL	-0.023	-0.400	0.566***	0.014**	-0.012*	0.046***	-0.639***
	(0.046)	(0.519)	(0.116)	(0.006)	(0.006)	(0.013)	(0.140)
TURNOVER	-5.587	-182.740***	17.146	1.094	-0.506	-8.494***	29.813***
	(4.430)	(57.972)	(13.659)	(0.709)	(0.516)	(1.561)	(10.934)
PRC	0.000	-0.021	-0.010	-0.001	0.000	0.001	-0.007
	(0.002)	(0.031)	(0.012)	(0.001)	(0.000)	(0.001)	(0.006)
Constant	0.584***	11.018***	4.772***	0.105***	0.155***	0.166***	0.599***
	(0.033)	(0.474)	(0.125)	(0.006)	(0.004)	(0.013)	(0.068)
#Obs	9,570	9,566	12,304	9,108	9,566	9,108	12,229
Panel B: With firm fixed effects							
TRADE	-0.066***	0.269	0.826***	0.025***	-0.007*	-0.009	-0.292***
	(0.020)	(0.456)	(0.139)	(0.006)	(0.004)	(0.008)	(0.081)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	9,570	9,566	12,304	9,108	9,566	9,108	12,229
Panel C: With time and firm fixed effects							
TRADE	-0.062***	0.121	0.809***	0.025***	-0.007*	-0.005	-0.286***
	(0.019)	(0.431)	(0.128)	(0.005)	(0.004)	(0.008)	(0.081)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	9,570	9,566	12,304	9,108	9,566	9,108	12,229
Panel D: With time and firm fixed effects (control group adjusted)							
TRADE	-0.013	0.034	0.795***	0.002	-0.000	-0.001	-0.284***
	(0.014)	(0.296)	(0.123)	(0.002)	(0.002)	(0.003)	(0.081)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	9,570	9,566	12,304	9,108	9,566	9,108	12,229

Table VI
Option-based Measures: Baseline Specification

The dependent variables are option-based information measures, measured at the company level at time t over the period 1995-2015. *TRADE* is an indicator variable equal to one for days of insider trading activity and zero for trading window of 35 to 21 days prior to the event day. 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** includes firm fixed effects. **Panel C** additionally includes time fixed effects. **In Panel D**, we additionally adjust measures of information subtracting average values of the portfolio of matched firms. Note that our results in Panel D do not report the coefficients for abnormal volume. The reason is that the estimation of this specific model is computationally highly demanding. In particular, to define the control group we would need to estimate the abnormal volume regression for each sub-period for each stock and since we have more than 3000 companies that are treated that would result in estimating millions of regression models. The matching is performed along 2-digit SIC industry code and the same market capitalization quintile. Standard errors (in parentheses) are clustered at the firm dimension. ***, **, * denote 1%, 5%, and 10% level of statistical significance, respectively.

Signal	Price					Volume		Both
	QS_o	QS_{otm}	IV_c	IV_p	IVS	AV_o	VR_{lo}	DI_o
Panel A: Baseline estimates								
TRADE	-0.021	-0.042*	0.013	0.008	0.004*	1.689***	-5.113***	-0.123***
	(0.020)	(0.025)	(0.012)	(0.013)	(0.002)	(0.493)	(1.869)	(0.024)
LNSIZE	-0.062**	-0.054	-0.135***	-0.125**	-0.003	-0.218	-8.032***	0.064*
	(0.029)	(0.034)	(0.047)	(0.053)	(0.003)	(0.288)	(2.098)	(0.036)
LNVOL	-0.023	-0.059*	0.106***	0.097**	0.004	-0.086	-1.359	-0.149***
	(0.030)	(0.035)	(0.036)	(0.041)	(0.003)	(0.146)	(2.181)	(0.041)
TURNOVER	-3.973*	-2.168	-3.000	-1.803	-0.586*	42.016*	-706.584***	2.443
	(2.239)	(2.604)	(2.835)	(3.248)	(0.306)	(21.585)	(167.744)	(2.338)
PRC	-0.002*	-0.003**	-0.000	0.000	-0.000	0.008	-0.083	-0.003***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.000)	(0.015)	(0.082)	(0.001)
Constant	0.644***	0.930***	0.570***	0.611***	-0.011***	-0.187*	37.127***	0.253***
	(0.019)	(0.023)	(0.015)	(0.017)	(0.002)	(0.096)	(1.409)	(0.026)
#Obs	8,396	8,396	8,275	8,136	8,020	8,477	8,488	7,571
Panel B: With firm fixed effects								
TRADE	-0.012	-0.039	0.031***	0.025***	0.004	1.810***	-3.213*	-0.102***
	(0.018)	(0.024)	(0.007)	(0.008)	(0.003)	(0.562)	(1.711)	(0.021)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	8,396	8,396	8,275	8,136	8,020	8,477	8,488	7,571
Panel C: With time and firm fixed effects								
TRADE	-0.019	-0.046**	0.028***	0.021***	0.004	1.731***	-3.436**	-0.103***
	(0.017)	(0.023)	(0.007)	(0.007)	(0.003)	(0.486)	(1.696)	(0.021)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	8,396	8,396	8,275	8,136	8,020	8,477	8,488	7,571
Panel D: With time and firm fixed effects (control group adjusted)								
TRADE	-0.024	-0.048**	0.030***	0.024***	0.005*	n/a	-3.466**	-0.078***
	(0.016)	(0.021)	(0.007)	(0.007)	(0.003)	n/a	(1.596)	(0.020)
Controls	Yes	Yes	Yes	Yes	Yes	n/a	Yes	Yes
#Obs	8,396	8,396	8,275	8,136	8,020	n/a	8,488	7,571

Table VII
Mixed Measures: Baseline Specification

The dependent variables are stock/option-based (mixed) information measures, measured at the company level at time t over the period 1995-2015. *TRADE* is an indicator variable equal to one for days of insider trading activity and zero for trading window of 35 to 21 days prior to the event day. 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** includes firm fixed effects. **Panel C** additionally includes time fixed effects. **In Panel D**, we additionally adjust measures of information subtracting average values of the portfolio of matched firms. The matching is performed along 2-digit SIC industry code and the same market capitalization quintile. Standard errors (in parentheses) are clustered at the firm dimension. ***, **, * denote 1%, 5%, and 10% level of statistical significance, respectively.

Signal	Price	Volume			Both	
	$QSR_{o\|s}$	$VR_{o\|s}$	$VR_{c\|s}$	$VR_{p\|s}$	$DI_{s\|o}$	$DI_{o\|s}$
Panel A: Baseline estimates						
TRADE	26.357	0.057***	0.045***	0.009***	-0.304***	-0.099***
	(40.997)	(0.010)	(0.008)	(0.003)	(0.060)	(0.023)
LNSIZE	288.939***	-0.015	-0.009	-0.006	-0.092	0.063
	(59.079)	(0.012)	(0.007)	(0.006)	(0.092)	(0.055)
LNVOL	-338.609***	0.020*	0.011	0.010*	-0.158	-0.201***
	(66.619)	(0.012)	(0.007)	(0.005)	(0.101)	(0.061)
TURNOVER	19,395.025***	-0.326	-0.192	-0.096	-8.067	4.548
	(4,394.799)	(1.046)	(0.648)	(0.482)	(6.229)	(3.505)
PRC	0.976	0.003***	0.002***	0.001***	-0.004	-0.004**
	(2.897)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)
Constant	672.912***	0.101***	0.063***	0.037***	0.767***	0.333***
	(39.860)	(0.007)	(0.004)	(0.003)	(0.060)	(0.035)
#Obs	8,146	8,488	8,487	8,488	7,670	8,244
Panel B: With firm fixed effects						
TRADE	-4.755	0.057***	0.044***	0.011***	-0.212***	-0.076***
	(33.963)	(0.009)	(0.007)	(0.003)	(0.055)	(0.023)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	8,146	8,488	8,487	8,488	7,670	8,244
Panel C: With time and firm fixed effects						
TRADE	-18.333	0.057***	0.044***	0.011***	-0.215***	-0.073***
	(31.906)	(0.009)	(0.007)	(0.003)	(0.055)	(0.023)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	8,146	8,488	8,487	8,488	7,670	8,244
Panel D: With time and firm fixed effects (control group adjusted)						
TRADE	-25.764	0.054***	0.041***	0.011***	-0.175***	-0.064***
	(29.506)	(0.009)	(0.007)	(0.003)	(0.053)	(0.022)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	8,146	8,488	8,487	8,488	7,670	8,244

Table VIII
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 IX
Conditioning on SEC Whistleblower Cases

The dependent variables are information measures. **Panel A** reports results for stock-based measures; **Panel B** for option-based measures; and **Panel C** for mixed measures. *TRADE* is an indicator variable equal to one for days of insider trading activity and zero for trading window of 35 to 21 days prior to the event day. 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. All panels include firm and time fixed effects and additionally adjust measures of information subtracting average values of the portfolio of matched firms. The matching is performed along 2-digit SIC industry code and the same market capitalization quintile. Standard errors (in parentheses) are clustered at the firm dimension. ***, **, * denote 1%, 5%, and 10% level of statistical significance, respectively.

	QS_s	PI_s	PR_s	RV_s	AOI_s	$Lambda_s$	DI_s
Panel A: Stock-based measures							
TRADE	-0.021	0.271	0.761***	0.005	-0.009**	-0.007	-0.167**
	(0.013)	(0.629)	(0.181)	(0.004)	(0.004)	(0.006)	(0.071)
WB	-0.096	-0.443	-0.064	-0.008	0.007	0.013*	0.066
	(0.073)	(0.408)	(0.496)	(0.005)	(0.007)	(0.008)	(0.051)
TRADE*WB	0.047	-0.433	0.068	-0.005	0.012	-0.002	0.170**
	(0.042)	(0.717)	(0.331)	(0.007)	(0.008)	(0.009)	(0.077)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	3,985	3,985	6,470	3,778	3,985	3,778	6,454

	QS_o	QS_{otm}	IV_c	IV_p	IVS	VR_{otm}	DI_o
Panel B: Option-based measures							
TRADE	-0.059**	-0.099***	0.046***	0.046***	0.007	-4.467*	-0.101***
	(0.029)	(0.038)	(0.011)	(0.011)	(0.006)	(2.587)	(0.037)
WB	-0.055	-0.129*	0.008	0.038	-0.005	9.548	0.021
	(0.045)	(0.066)	(0.038)	(0.045)	(0.006)	(7.086)	(0.040)
TRADE*WB	0.046	0.087	-0.025	-0.029	-0.004	0.358	0.021
	(0.045)	(0.058)	(0.022)	(0.029)	(0.007)	(4.470)	(0.053)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	4,778	4,778	4,684	4,580	4,402	4,870	4,283

	$QSR_{o\|s}$	$VR_{o\|s}$	$VR_{c\|s}$	$VR_{p\|s}$	$DI_{s\|o}$	$DI_{o\|s}$
Panel C: Mixed measures						
TRADE	-59.779	0.063***	0.044***	0.020***	-0.207**	-0.116***
	(58.730)	(0.014)	(0.010)	(0.006)	(0.098)	(0.037)
WB	132.410	0.034	0.011	0.026**	0.227	-0.062**
	(93.533)	(0.037)	(0.026)	(0.013)	(0.169)	(0.029)
TRADE*WB	75.456	-0.045	-0.023	-0.022**	0.047	0.035
	(85.954)	(0.031)	(0.021)	(0.011)	(0.136)	(0.054)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	4,712	4,870	4,869	4,870	4,353	4,663

Table X
Conditioning on Case Complexity

The dependent variables are information measures. **Panel A** reports results for stock-based measures; **Panel B** for option-based measures; and **Panel C** for mixed measures. *TRADE* is an indicator variable equal to one for days of insider trading activity and zero for trading window of 35 to 21 days prior to the event day. 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. All panels include firm and time fixed effects and additionally adjust measures of information subtracting average values of the portfolio of matched firms. The matching is performed along 2-digit SIC industry code and the same market capitalization quintile. Standard errors (in parentheses) are clustered at the firm dimension. ***, **, * denote 1%, 5%, and 10% level of statistical significance, respectively.

	QS_s	PI_s	PR_s	RV_s	AOI_s	$Lambda_s$	DI_s
Panel A: Stock-based measures							
TRADE	-0.014	-0.003	0.949***	0.008***	-0.002	-0.001	-0.165**
	(0.022)	(0.005)	(0.167)	(0.003)	(0.005)	(0.005)	(0.072)
SIMPLE	0.181	-0.002	-0.578	-0.011	0.004	0.003	0.123
	(0.171)	(0.011)	(0.412)	(0.015)	(0.014)	(0.017)	(0.146)
TRADE*SIMPLE	0.003	0.006	-0.287	-0.011***	0.004	0.001	-0.221
	(0.027)	(0.006)	(0.237)	(0.004)	(0.005)	(0.006)	(0.156)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	9,570	9,566	12,304	9,108	9,566	9,108	12,229

	QS_o	QS_{otm}	IV_c	IV_p	IVS	VR_{otm}	DI_o
Panel B: Option-based measures							
TRADE	-0.037	-0.064*	0.029***	0.032**	0.004	-4.074	-0.108***
	(0.024)	(0.033)	(0.009)	(0.013)	(0.003)	(2.602)	(0.035)
SIMPLE	0.037	0.057	-0.054	-0.051	0.006	0.700	-0.057**
	(0.089)	(0.140)	(0.066)	(0.048)	(0.008)	(5.202)	(0.025)
TRADE*SIMPLE	0.025	0.030	0.002	-0.014	0.001	1.134	0.057
	(0.032)	(0.043)	(0.014)	(0.017)	(0.005)	(3.152)	(0.042)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	8,396	8,396	8,275	8,136	8,020	8,488	7,571

	$QSR_{o\|s}$	$VR_{o\|s}$	$VR_{c\|s}$	$VR_{p\|s}$	$DI_{s\|o}$	$DI_{o\|s}$
Panel C: Mixed measures						
TRADE	-65.728	0.046***	0.036***	0.009*	-0.198**	-0.065*
	(47.275)	(0.013)	(0.009)	(0.005)	(0.090)	(0.038)
SIMPLE	141.576	-0.066	-0.027	-0.037	0.127	0.095
	(133.218)	(0.061)	(0.036)	(0.029)	(0.084)	(0.068)
TRADE*SIMPLE	75.315	0.013	0.009	0.004	0.044	0.002
	(59.609)	(0.019)	(0.014)	(0.007)	(0.109)	(0.046)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	8,146	8,488	8,487	8,488	7,670	8,244

Table XI
Conditioning on Signal Strength

The dependent variables are information measures. **Panel A** reports results for stock-based measures; **Panel B** for option-based measures; and **Panel C** for mixed measures. *TRADE* is an indicator variable equal to one for days of insider trading activity and zero for trading window of 35 to 21 days prior to the event day. 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. All panels include firm and time fixed effects and additionally adjust measures of information subtracting average values of the portfolio of matched firms. The matching is performed along 2-digit SIC industry code and the same market capitalization quintile. Standard errors (in parentheses) are clustered at the firm dimension. ***, **, * denote 1%, 5%, and 10% level of statistical significance, respectively.

	QS_s	PI_s	PR_s	RV_s	AOI_s	$Lambda_s$	DI_s
Panel A: Stock-based measures							
TRADE	-0.031	0.932*	0.721***	0.002	-0.002	-0.000	-0.191*
	(0.024)	(0.536)	(0.172)	(0.003)	(0.003)	(0.003)	(0.106)
STRENGTH	0.000**	0.006*	-0.004***	-0.000***	0.000	0.000	0.001
	(0.000)	(0.003)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
TRADE*STRENGTH	0.000	-0.020*	0.003	0.000	0.000	-0.000	-0.003*
	(0.001)	(0.012)	(0.003)	(0.000)	(0.000)	(0.000)	(0.002)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	8,537	8,533	10,956	8,122	8,533	8,122	10,899

	QS_o	QS_{otm}	IV_c	IV_p	IVS	VR_{otm}	DI_o
Panel B: Option-based measures							
TRADE	-0.048**	-0.078***	0.024***	0.020**	0.005*	-2.782	-0.067**
	(0.019)	(0.024)	(0.008)	(0.009)	(0.003)	(1.826)	(0.032)
STRENGTH	0.001***	0.001***	-0.001***	-0.001**	-0.000	0.030***	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.007)	(0.001)
TRADE*STRENGTH	0.000	0.000	0.000	0.000	-0.000	-0.026	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.021)	(0.001)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	7,395	7,395	7,295	7,156	7,093	7,487	6,629

	$QSR_{o\|s}$	$VR_{o\|s}$	$VR_{c\|s}$	$VR_{p\|s}$	$DI_{s\|o}$	$DI_{o\|s}$
Panel C: Mixed measures						
TRADE	-33.328	0.060***	0.046***	0.012***	-0.086***	-0.219***
	(34.721)	(0.010)	(0.008)	(0.004)	(0.032)	(0.060)
STRENGTH	0.061	-0.000***	-0.000***	-0.000***	-0.000	0.002***
	(0.099)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
TRADE*STRENGTH	0.416	-0.000	-0.000	-0.000	0.000	-0.000
	(0.320)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	7,179	7,487	7,486	7,487	7,266	6,713

Table XII
Option-based Measures: Maturity and Moneyness

The dependent variables are option-based information measures, measured at the company level at time t over the period 1995-2015. *TRADE* is an indicator variable equal to one for days of insider trading activity and zero for trading window of 35 to 21 days prior to the event day. 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** includes firm fixed effects. **Panel C** additionally includes time fixed effects. **In Panel D**, we additionally adjust measures of information subtracting average values of the portfolio of matched firms. The matching is performed along 2-digit SIC industry code and the same market capitalization quintile. Standard errors (in parentheses) are clustered at the firm dimension. ***, **, * denote 1%, 5%, and 10% level of statistical significance, respectively.

	Maturity				Moneyness		
	<10d	10-30d	31-60d	>60d	ITM	ATM	OTM
Panel A: $VR_{o\|s}$ with time and firm fixed effects							
TRADE	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: $VR_{o\|s}$ with time and firm fixed effects (control group adjusted)							
TRADE	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 XIII
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 XIV

Conditioning on Informed Trading Intensity

This table presents separate results for trades with low (below median) and high (above median) trading intensity. Trading intensity is defined as the ratio of aggregate insider trades relative to the total volume of trades measured on a given trading day. The dependent variables are information measures. **Panels A and B** report stock-based measures. **Panels C and D** report option-based measures. **Panels E and F** report stock- and option-based measures. *TRADE* is an indicator variable equal to one for days of insider trading activity and zero for trading window of 35 to 21 days prior to the event day. 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. All panels include firm and time fixed effects and additionally adjust measures of information subtracting average values of the portfolio of matched firms. The matching is performed along 2-digit SIC industry code and the same market capitalization quintile. Standard errors (in parentheses) are clustered at the firm dimension. ***, **, * denote 1%, 5%, and 10% level of statistical significance, respectively.

	QS_s	PI_s	PR_s	RV_s	AOI_s	$Lambda_s$	DI_s
Panel A: Stock-based measures: Low Intensity							
TRADE	-0.022**	0.036	0.733***	0.002	0.001	-0.006**	-0.051
	(0.009)	(0.365)	(0.172)	(0.003)	(0.003)	(0.003)	(0.044)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	3,950	3,950	4,778	3,855	3,950	3,855	4,778
Panel B: Stock-based measures: High Intensity							
TRADE	-0.017	0.110	1.074***	0.003	0.001	0.007	-0.782***
	(0.032)	(0.602)	(0.217)	(0.003)	(0.005)	(0.005)	(0.232)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	3,614	3,610	4,550	3,328	3,610	3,328	4,499

	QS_o	QS_{otm}	IV_c	IV_p	IVS	VR_{otm}	DI_o
Panel C: Option-based measures: Low Intensity							
TRADE	-0.024	-0.074*	0.017*	0.021	0.005	-5.489	-0.059***
	(0.026)	(0.038)	(0.011)	(0.023)	(0.004)	(3.588)	(0.019)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	1,494	1,494	1,525	1,520	1,481	1,531	1,478
Panel D: Option-based measures: High Intensity							
TRADE	-0.046	-0.055	0.024**	0.013	0.004	-3.688	-0.115**
	(0.029)	(0.039)	(0.010)	(0.009)	(0.003)	(3.092)	(0.048)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	1,913	1,913	1,947	1,926	1,711	1,947	1,801

	$QSR_{o\|s}$	$VR_{o\|s}$	$VR_{c\|s}$	$VR_{p\|s}$	$DI_{s\|o}$	$DI_{o\|s}$
Panel E: Mixed measures: Low Intensity						
TRADE	-61.129	0.084***	0.058***	0.023**	-0.017	-0.159***
	(59.198)	(0.030)	(0.020)	(0.010)	(0.014)	(0.050)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	1,467	1,531	1,531	1,531	1,520	1,488
Panel F: Mixed measures: High Intensity						
TRADE	-19.269	0.098***	0.081***	0.013**	-0.025	-0.337**
	(81.140)	(0.022)	(0.018)	(0.005)	(0.054)	(0.133)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	1,829	1,947	1,947	1,947	1,944	1,804

Table XV

Conditioning on Insider Sophistication

This table presents separate results for traders executed by sophisticated and unsophisticated investors. The dependent variables are information measures. **Panels A and B** report stock-based measures. **Panels C and D** report option-based measures. **Panels E and F** report mixed measures. *TRADE* is an indicator variable equal to one for days of insider trading activity and zero for trading window of 35 to 21 days prior to the event day. 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. All panels include firm and time fixed effects and additionally adjust measures of information subtracting average values of the portfolio of matched firms. The matching is performed along 2-digit SIC industry code and the same market capitalization quintile. Standard errors (in parentheses) are clustered at the firm dimension. ***, **, * denote 1%, 5%, and 10% level of statistical significance, respectively.

	QS_s	PI_s	PR_s	RV_s	AOI_s	$Lambda_s$	DI_s
Panel A: Stock-based measures: Unsophisticated Traders							
TRADE	-0.028**	0.012	0.839***	0.008**	0.002	-0.000	-0.282**
	(0.013)	(0.417)	(0.182)	(0.004)	(0.003)	(0.005)	(0.132)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	3,608	3,607	5,043	3,443	3,607	3,443	5,003
Panel B: Stock-based measures: Sophisticated Traders							
TRADE	-0.006	0.270	0.762***	0.002	0.001	0.003	-0.209***
	(0.025)	(0.414)	(0.207)	(0.003)	(0.004)	(0.003)	(0.077)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	4,165	4,164	5,200	3,953	4,164	3,953	5,184

	QS_o	QS_{otm}	IV_c	IV_p	IVS	VR_{otm}	DI_o
Panel C: Option-based measures: Unsophisticated Traders							
TRADE	-0.036	-0.083***	0.048***	0.039**	0.003	-2.355	-0.067*
	(0.022)	(0.028)	(0.011)	(0.016)	(0.004)	(2.259)	(0.037)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	3,361	3,361	3,303	3,239	3,207	3,417	3,025
Panel D: Option-based measures: Sophisticated Traders							
TRADE	0.009	-0.007	0.014	0.012	0.007	-3.371	-0.104***
	(0.023)	(0.039)	(0.010)	(0.010)	(0.005)	(2.828)	(0.036)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	3,522	3,522	3,516	3,472	3,348	3,557	3,252

	$QSR_{o\|s}$	$VR_{o\|s}$	$VR_{c\|s}$	$VR_{p\|s}$	$DI_{s\|o}$	$DI_{o\|s}$
Panel E: Mixed measures: Unsophisticated Traders						
TRADE	-54.835	0.072***	0.052***	0.016***	-0.052	-0.114
	(45.461)	(0.018)	(0.013)	(0.006)	(0.039)	(0.098)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	3,271	3,417	3,416	3,417	3,289	3,080
Panel F: Mixed measures: Sophisticated Traders						
TRADE	48.714	0.022***	0.020***	0.002	-0.070***	-0.207**
	(52.394)	(0.008)	(0.006)	(0.004)	(0.026)	(0.091)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	3,393	3,557	3,557	3,557	3,509	3,278

Table XVI
Conditioning on Event Type

This table presents separate results for mergers and acquisitions and earnings announcements. The dependent variables are information measures. **Panels A and B** report stock-based measures. **Panels C and D** report option-based measures. **Panels E and F** report stock- and option-based measures. *TRADE* is an indicator variable equal to one for days of insider trading activity and zero for trading window of 35 to 21 days prior to the event day. 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. All panels include firm and time fixed effects and additionally adjust measures of information subtracting average values of the portfolio of matched firms. The matching is performed along 2-digit SIC industry code and the same market capitalization quintile. Standard errors (in parentheses) are clustered at the firm dimension. ***, **, * denote 1%, 5%, and 10% level of statistical significance, respectively.

	QS_s	PI_s	PR_s	RV_s	AOI_s	$Lambda_s$	DI_s
Panel A: Stock-based measures: Mergers and acquisitions							
TRADE	-0.005	0.212	0.636***	-0.001	0.001	-0.002	-0.393***
	(0.016)	(0.387)	(0.133)	(0.002)	(0.003)	(0.004)	(0.104)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	5,265	5,261	6,707	4,992	5,261	4,992	6,644
Panel B: Stock-based measures: Earnings announcements							
TRADE	-0.006	0.370	0.085	-0.001	0.001	0.000	-0.029
	(0.013)	(0.324)	(0.367)	(0.005)	(0.004)	(0.003)	(0.031)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	1,318	1,318	1,762	1,278	1,318	1,278	1,762

	QS_o	QS_{otm}	IV_c	IV_p	IVS	VR_{otm}	DI_o
Panel C: Option-based measures: Mergers and acquisitions							
TRADE	-0.036	-0.082***	0.030***	0.026**	0.006**	-4.972**	-0.103***
	(0.023)	(0.030)	(0.009)	(0.011)	(0.003)	(2.200)	(0.028)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	4,508	4,508	4,433	4,332	4,309	4,529	3,897
Panel D: Option-based measures: Earnings announcements							
TRADE	-0.008	-0.016	0.015	0.004	0.000	2.581	-0.105**
	(0.033)	(0.043)	(0.010)	(0.010)	(0.004)	(3.193)	(0.051)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	1,555	1,555	1,603	1,583	1,432	1,609	1,527

	$QSR_{o\|s}$	$VR_{o\|s}$	$VR_{c\|s}$	$VR_{p\|s}$	$DI_{s\|o}$	$DI_{o\|s}$
Panel E: Mixed measures: Mergers and acquisitions						
TRADE	-43.013	0.061***	0.050***	0.008*	-0.198**	-0.065*
	(42.722)	(0.014)	(0.010)	(0.004)	(0.077)	(0.034)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	4,400	4,529	4,529	4,529	3,942	4,414
Panel F: Mixed measures: Earnings announcements						
TRADE	-19.817	0.037***	0.021**	0.017**	-0.243**	-0.104**
	(73.433)	(0.011)	(0.009)	(0.007)	(0.103)	(0.046)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	1,506	1,609	1,609	1,609	1,530	1,600

Table XVII
Conditioning on Information Direction

This table presents separate results for positive and negative information events. The dependent variables are information measures. **Panels A and B** report results for stock-based measures. **Panels C and D** report results for option-based measures. **Panels E and F** report results for mixed measures. *TRADE* is an indicator variable equal to one for days of insider trading activity and zero for trading window of 35 to 21 days prior to the event day. 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. All panels include firm and time fixed effects and additionally adjust measures of information subtracting average values of the portfolio of matched firms. The matching is performed along 2-digit SIC industry code and the same market capitalization quintile. Standard errors (in parentheses) are clustered at the firm dimension. ***, **, * denote 1%, 5%, and 10% level of statistical significance, respectively.

	QS_s	PI_s	PR_s	RV_s	AOI_s	$Lambda_s$	DI_s
Panel A: Stock-based measures: Positive News							
TRADE	-0.005	0.080	0.789***	0.002	0.001	-0.002	-0.322***
	(0.014)	(0.336)	(0.126)	(0.002)	(0.003)	(0.003)	(0.083)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	6,973	6,969	8,954	6,650	6,969	6,650	8,887
Panel B: Stock-based measures: Negative News							
TRADE	-0.050	-0.233	0.824**	0.001	-0.005	0.001	-0.172
	(0.038)	(0.610)	(0.330)	(0.006)	(0.005)	(0.004)	(0.221)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	2,581	2,581	3,334	2,443	2,581	2,443	3,326
	QS_o	QS_{otm}	IV_c	IV_p	IVS	VR_{otm}	DI_o
Panel C: Option-based measures: Positive News							
TRADE	-0.026	-0.049**	0.036***	0.030***	0.006**	-4.037**	-0.094***
	(0.017)	(0.023)	(0.008)	(0.009)	(0.003)	(1.874)	(0.024)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	6,235	6,235	6,163	6,041	5,921	6,310	5,531
Panel D: Option-based measures: Negative News							
TRADE	-0.016	-0.053	0.009	0.009	-0.003	-1.529	-0.015
	(0.031)	(0.048)	(0.013)	(0.013)	(0.003)	(2.458)	(0.029)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	2,145	2,145	2,112	2,094	2,083	2,162	2,040
	$QSR_{o\|s}$	$VR_{o\|s}$	$VR_{c\|s}$	$VR_{p\|s}$	$DI_{s\|o}$	$DI_{o\|s}$	
Panel E: Stock- and Option-based measures: Positive News							
TRADE	-9.736	0.062***	0.050***	0.010***	-0.205***	-0.073***	
	(35.163)	(0.011)	(0.008)	(0.003)	(0.065)	(0.028)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	
#Obs	6,043	6,310	6,309	6,310	5,611	6,140	
Panel F: Stock- and Option-based measures: Negative News							
TRADE	-83.357	0.025***	0.011*	0.014**	-0.051	-0.021	
	(67.318)	(0.009)	(0.006)	(0.007)	(0.055)	(0.015)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	
#Obs	2,087	2,162	2,162	2,162	2,059	2,104	

Table XVIII
Volume Ratios Net of Insider Trades

The dependent variables are volume ratios net of insider traders' trades, measured at the company level at time t over the period 1995-2015. $TRADE$ is an indicator variable equal to one for days of insider trading activity and zero for trading window of 35 to 21 days prior to the event day. 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. We include time and firm-fixed effects and additionally adjust measures of information subtracting average values of the portfolio of matched firms. The matching is performed along 2-digit SIC industry code and the same market capitalization quintile. Standard errors (in parentheses) are clustered at the firm dimension. ***, **, * denote 1%, 5%, and 10% level of statistical significance, respectively.

	$VR_{o\|s}$	$VR_{c\|s}$	$VR_{p\|s}$
TRADE	0.045***	0.034***	0.010***
	(0.008)	(0.006)	(0.003)
Controls	Yes	Yes	Yes
#Obs	8,488	8,487	8,488