Chasing Private Information*

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Abstract

Using a novel sample of 3,586 equity and option trades based on material and nonpublic information, we examine whether asset prices and trading volume reveal to markets information about the presence of informed trading. We find that information embedded in equity (option) markets offers a generally weaker (stronger) signal of private information. The most robust metrics combine both option and stock volume, especially those using leveraged and short-term options. Further, we show that the patterns showing how information is revealed to markets do not depend on whether informed traders strategically delay their trades upon receiving information about the firm. Finally, we document significant information spillovers from equity to option markets, but not vice versa. Overall, our results provide new guidance in the search for private information.

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1 Introduction

Asymmetric information is ubiquitous in economics and finance. In a world with asymmetric information, uninformed investors want to know when informed investors trade when deciding about their own trades. Various information-based trade theories argue that uninformed investors update their beliefs about informed trading based on publicly observed signals, such as trading volume or market prices.[1] While these signals may provide useful guidance in the quest for 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 secret and material information. Our sample of SEC cases involves a large number of trades in several hundred companies over the period 1995-2012. 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.

Guided by prior theoretical and empirical research, we consider three types of information signals: (i) those based on aggregate trading volume, (ii) those based on asset prices, and (iii) those combining volume and prices. Because market participants can exploit their information advantage using different assets, we assess information measures that are based on stock-level as well as on option-level data. Our results carry three main messages: (1) options market generally reveals 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 signals utilize information

[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).

that spans both option and stock markets.

Our setting is based on a comprehensive sample of 370 insider trading cases filed by the SEC over the period 2001-2012. Each case includes a detailed description of situations in which individuals execute their trades using material and nonpublic information. An example of such trade would be buying stocks of a company by a family member of the company's CEO based on the private information about the exceptional quality of the company's earnings reported in the future. We collect detailed information about insider traders, the companies and instruments they trade, the exact dates of the trade and information acquisition, and the corporate events to which the trades correspond. We additionally collect information about the dates when such information is released to the market. Importantly, there is no uncertainty whether information underlying the trade is private or not. Overall, our final sample covers 3,586 trades in 547 companies that represent the vast majority of industry sectors.

At the outset, we evaluate the strength of the information the insiders are trading on by calculating hypothetical returns (excluding dividends) a trader would realize if she initiated her trade at the open of the day insiders trade on private information and closed it at the open of the day following the public information disclosure. We show that, on average, such returns equal almost 50% for the news that is positive and over -20% for the news that is negative. Both results are economically large especially since they accrue over a relatively short window of 7 days on average. They are also an order of magnitude larger than the returns realized by typical informed investors, such as 13D filers.

Our subsequent empirical tests utilize an event-study framework, in which we compare the values of information measures for companies traded by informed investors on insider trading days 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 event. 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 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. 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 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. Next, we entertain similar tests for measures derived from options data. We find that, on average, option-based measures are more likely to reveal private information to markets. Four out of eight measures we consider are statistically significant in the most comprehensive specification that considers fixed effects and the control group. The most significant measures include implied volatility and option illiquidity measure. Finally, we consider measures that combine data coming both from 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, 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 traders.

To provide additional cross-sectional evaluation of our best information measures, that is, those utilizing volume from options and stocks markets, we analyze the cross-section of option contracts with respect to their maturity and moneyness dimensions. Our results are strongest for measures that consider relatively short-term contracts (between 10 and 60 days) and levered (out-of-the money) contracts, which is consistent with the view that informed trading is primarily located in contracts, which are relatively inexpensive to access.

Since our sample consists solely of uncovered 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, if one believes that the SEC successfully acts upon 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] Second, the most robust stock-based measure, daily illiquidity, moves in the opposite direction to what informed trading would have predicted. It displays 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. Third, we find that certain option measures in fact detect information even when no option trading is done by insiders. Finally, in Section 5.3, we show that our results remain unchanged for the sample of cases involving multiple traded firms. In particular, if SEC's investigation were indeed triggered by the unusual trading behavior in shares of a given company, it is much less likely that such unusual trading would happen for multiple firms at the same time. Instead, a more likely possibility is that other trades would be discovered through the investigation process of an initial lead.

In our subsequent analysis, we shed more light on the economic forces behind our results. First, we examine whether the patterns we document are equilibrium outcomes of the strategic behavior of informed investors who aim to disguise their trades or trade opportunistically when market conditions are most favorable. Such mechanism has been recently proposed in a study by Collin-Dufresne and Fos (2015) who argue that trades by activist investors documented in their 13D filings are positively related to market liquidity because such traders execute their trades *strategically*. The granularity of our data allows us to test the hypothesis of strategic motives for trading more directly. We test the hypothesis in three ways. First, we look for any evidence of timing in our main results based on the sign of the coefficient of *Trade*. If traders use their information strategically, one should expect that the coefficient be negative, that is, market illiquidity should be lower on days when informed trading takes place. Of the eight measures that are statistically significant, only two–daily illiquidity and option quoted spread–are negative. The remaining six measures are positive. Hence, the evidence in favor of market timing is quite weak to begin with. Second, we

[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.

take advantage of the fact that we can observe when informed investors *acquire* information and when they *use* it. We argue that strategic motives are less likely if the distance between the two dates is short. In our sample, the median distance between the information acquisition and its use is three days, which suggests that many traders use their information non strategically. Moreover, while conditioning our main results on a short information horizon slightly reduces the significance of *Trade* coefficients, their signs remain the same. Third, we also consider settings in which we believe strategic trading would be less likely. These include cases in which a particular trader trades a small number of times, a company is traded by only a few insiders, a legal case involves only a few trades, or a trade is executed by less sophisticated traders. In all these cases, we find that the significance of our results remains unchanged. Overall, our results cast doubts over the strategic timing hypothesis.

Another economic mechanism we explore is that of information spillovers across different assets markets. One possibility is that trades executed in a given asset market would be only informative in *the same* asset market. An alternative possibility is that trades executed in one market may reveal private information in another market. This might, for example, happen if information in one market is more beneficial to exploit in another market. For example, investors who obtain information in stock market may want to lever it up in option market. Alternatively, market makers might hedge their positions in equity markets based on the information they observe in option market. We evaluate the presence of such cross-market linkages by conditioning our results on trades that are executed solely in the stock market or solely executed in the option market. We find that option-based measures reveal private information even if the informed trades are executed using only stocks. At the same time, we do not find significant information spillovers from trades originating in options market to stock market as only one of the stock-based measures that are related to option-only trades is significant. These results suggest that the decision of informed investors where to execute their trades might be strategic in nature.

We conduct a number of additional tests. First, we find that information embedded in prices and volume reveals most information ahead of future mergers and acquisitions and earnings announcements. Second, market signals reveal more information in anticipation of positive news rather than negative news. Third, more information is revealed for companies whose shares are primarily listed on Nasdaq or NYSE. Finally, using signed option measures, based on the data from International

Securities Exchange, we find that option-based measures that originate on the buy side and are based on open quotes and call contracts are most informative.

Related Literature

Our paper is related to three strands of literature. First, we contribute to the literature on the informational content of stock and option prices. The 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]

Second, we contribute to the literature on private information in trading. A large body of papers analyze and apply the probability of informed trading model or PIN (Easley et al. (1996a,b)). The information structure 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]

A second research context in which an attempt has been made to identify private information has been the asset management industry (e.g., Kacperczyk and Seru, 2007; Cohen et al., 2008; and Kacperczyk et al., 2014). In addition, Cohen et al. (2012) attribute private information to a non-systematic component of corporate insiders' trades. Boulatov et al. (2013) and Hendershott et al. (2015) identify information based on institutional order flow. 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. Although several

[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.

[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).

of these studies consider plausible proxies for private information, they are ultimately unable to provide a definite answer whether certain individuals indeed acted upon private information when trading.

Finally, we also contribute to the literature on the market impact of insider trading, especially that which explicitly considers SEC 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 (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 closest papers to ours are two recent studies by Collin-Dufresne and Fos (2015) and Collin-Dufresne et al. (2015), which examine the information content of prices based on investment decisions of large activist investors reported in SEC 13D filings. The first and most distinct feature of our study is that the informed traders we analyze trade using previously obtained nonpublic and material information. In contrast, 13D filings need not signal informed trades. In fact, the majority of activist trades reflect a decision to affect a firm's future and not an explicit reaction to private information. Also, the trading patterns of 13D investors are very different from those we document in our sample. For example, the activists do not trade much option contracts, a surprising fact given that options offer an easy way to leverage up information advantage. Moreover, even if some activist investors may indeed have the power to produce nonpublic information due to their power to affect future corporate decisions, the success of such actions is ex ante uncertain and may in fact be negated ex post.[9] To the best of our knowledge, the ability to isolate the sample of unequivocal material and nonpublic information trades both in stocks and options is a unique contribution of our study relative to all other studies on the topic.

More germane to our empirical context, the granularity of our data also allows us to study various economically relevant issues. Since our sample includes both stock and option trades, we are able to compare the quality of signals originating in both markets and show the transmission

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

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

[9] A case in point is the story of Herbalife in which two activist investors, Carl Icahn and Bill Ackman, took perfectly opposite views on the future of the company and placed directionally opposite trades.

mechanism by which information travels from one market to another. Further, we present new results that information contained in volume is more informative about informed trading than are prices and transaction costs. Finally, given that we observe specific and mostly distinct dates when investors gather and use their information, we are able to trace down in greater detail the mechanism by which information is revealed to markets. Specifically, the referenced study shows that the trades of 13D investors do not reflect private information in that they correlate negatively with measures of illiquidity and adverse selection. It attributes this pattern to strategic investor behavior, reflected by trading on days with high liquidity. While our paper confirms the finding that stock-based measures display higher liquidity levels on insider trading days, we also show that information measures, qualitatively, display the same behavior regardless of whether traders wait to use their information or not. Consequently, we argue that the documented negative correlation cannot be merely explained by strategic trading delays and requires further investigation.

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 4 describes the sample of insider trading cases which is then taken into an empirical testing in Section 5. Section 6 concludes. Detailed description of the data is provided in the Appendix.

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.

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

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 (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.[10]

Price Range (PR) We define the daily price range simply as

[10] 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.

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

where $a_{\text{max,t}}$ and $b_{\text{min,t}}$ 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 (*RV*) We also consider the standard realized variance (RV) specification (e.g., Barndorff-Nielsen and Shephard (2002)) based on 30-minute intervals.

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.[11] 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 (*AOI*) The absolute order imbalance is defined as

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

[11]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.

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 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.[12]

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

$$DI_{s,t} = \frac{|r_t|}{vol_t}. \tag{1}$$

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

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 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

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

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 ($OMIV$)

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

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.[13]

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. [14]

[13] 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.

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

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).

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.[15] 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

[15] 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 5, our OS results are indeed stronger for positive news.

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

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

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

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 Information Measures around Earnings Announcements

A traditional approach to evaluate the quality of any information measure has been to examine their dynamics around events when information is publicly revealed to markets. The most popular information events have been by far earnings announcements and mergers and the literature has focused on the behavior of PIN measure around these events.[16] In this Section, we examine the behavior of a broader set of measures (stock-based, option-based, and stock and option based) previously defined in Section 2 around earnings announcements using two event windows related to information events: (i) within 3 days before the earnings release and (ii) within 4 to 10 days before. These choices are motivated by the fact that many investors may enter the markets right before the information is released and their entry might reflect differences in opinions or 'gambling' rather than motivated by private information. In turn, investors who trade earlier are more likely to be motivated by information. This distinction is particularly relevant for scheduled information releases, such as earnings announcements, and is a way to ascertain the source of variation in a given information measure. Following the typical event-study setup, for both event windows, we specify the pre-event window to be include 20 to 10 days before information release to account for the time-series effects that are unrelated to the information event per se. Specifically, we define an indicator variable *Trade*, equal to one within the event window and equal to zero for observations

[16] Aktas et al. (2007) find that PIN is higher after merger announcements than before, partially as a result of increases in PIN model's α. Using a model with time-varying trade arrival rates, Easley et al. (2008) show that the PIN variation around earnings announcement dates happens within a very narrow window of ± 7 days before and after the announcement. See also Benos and Jochec (2007), Duarte et al. (2015), and Brennan et al. (2015).

falling in the pre-event window.

Our data include a comprehensive set of all earnings announcement and merger dates spanning the period of 1995-2012. The earnings announcement dates are from Compustat and the merger announcement dates are from SDC Platinum. In order to detect any abnormality in their behavior around information events we estimate the regression model with information measure as a dependent variable and *Trade* being a main control. If the measure displays any abnormality we should expect the coefficient of *Trade* to be statistically significant. To soak up the variation in our outcome variable we include additional controls: natural logarithm of market capitalization, natural logarithm of stock volume, turnover, and stock price. All controls are pre-determined with respect to the event window and set at their values at 20 days before the event.

In our formal test, we compare each firm i that is making a corporate announcement in a given period t to a matched portfolio of firms with similar characteristics. 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 ($CAIM$). This estimation approach is akin to a standard difference-in-differences estimation. To account for a serial correlation in the residuals we cluster standard errors at the firm level. Formally, we estimate the following regression model for each set of information measures for two different event windows k:

$$CAIM_{it,t-k} = a + b\times\text{Trade}_{it,t-k}+c\times\text{Controls}_{it-20}+\text{d}_i+\text{ e}_t+\text{ error}_{it,t-k}. \tag{2}$$

The results for earnings announcements are presented in Table VI. In Panels A-C, we present the results for the event window of -3 to 0 days before corporate announcement. The results indicate a strong abnormal behavior of several information measures in this short event window. This is especially true for option-based and mixed measures, for which most coefficients of *Trade* are statistically significant. In turn, among stock-based measures, only three *PI*, *PR*, and *DI* are statistically different from pre-event values. A common interpretation of these results would be that some of the measures suggest the existence of informed trading prior to earnings announcements. However, events such as earnings are pre-scheduled as such many investors may behave like informed ones even though they may not carry any private information. This behavior is especially likely right before the events when transaction costs are particularly low.

To assess the feasibility of this hypothesis, we repeat our estimation process for the event-window of 4 to 10 days prior to public release. Panels D-F show the results for the same set of information measures. We observe a significant weakening of the previously reported abnormalities. This is especially true for mixed measures, all of which become insignificant. These findings cast some doubt on the interpretation of our earlier results as being indicative of informed trading. On the one hand, information could only flow in in the short window before the announcements. On the other hand, it could be that the measures reflect differences of opinions rather than pure information. Given that information sets of investors cannot be observed based on such results one cannot conclusively argue for either of the two possibilities. This is why we turn into our empirical setting of insider trading in which information sets of investors can be observed.

4 Insider Trading Sample

4.1 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.

4.2 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.[17] 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 2012. 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 370 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

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

single transaction record for which we can observe a date and a trading instrument (e.g., stock and 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.

4.3 Descriptive Statistics

Our data collection procedure yields 370 legal cases. Table IV 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 (54.49%) followed by earnings announcements (18.92%). The categories Business Events and Corporate Events (17.30%) 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 V, 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 3,586 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 (71.22%) and options (27.82%). 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 3,020 buys (83.34%) and 566 sells. In Panel C, we classify trades with respect to the exchange in which the company equity is listed. The two dominant exchanges are NYSE and Nasdaq. This classification is unique until 2007 when Regulation NMS was introduced and then we use the original listing place for any cross-listing after 2007. In Panel D, we further 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 1995-2012. We observe a relatively small number of trades in the 1990s and then towards the end of our sample in 2012. 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 E, we further show that the distribution of insider trades is fairly even across calendar months. This feature suggests that the trades are unlikely by cyclicality in corporate or macroeconomic announcements. In Panel F, we also 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 G, 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 1 day. In turn, the median number of days from trade till information event is 7 days. Further, a median trader in our sample executes 7 trades with the maximum of 73 days. A median firm receives 13 trades and a median legal case involves 2 firms. A median age of tippers and traders is almost identical and equal to 44 years. The vast majority of tippers and traders in our sample are male. The profits reported by traders are highly skewed with the average of $831,000 and the median of $93,500. 49% of traders report at least $100,000 in profits.

Table II
Measuring the Information Content of Trades

	Positive News	Negative News	Aggregate	Positive
	Illegal Insider Trading			13D Filers
Mean Return (%)	47.756***	-21.938***	42.348***	4.694***
	(4.613)	(2.458)	(3.786)	(0.839)
Median Return (%)	36.111***	-16.706***	32.868***	2.235***
	(2.466)	(3.650)	(2.162)	(0.202)
#Obs	1,570	416	1,986	2,193

The return is computed from open price on trade day to close price on disclosure date (e.g., corporate announcement for insider traders and filing date for 13D traders)

4.4 How Much Private Information?

Our empirical design relies on the work of the SEC to verify the material and non-public nature of the information received by the involved traders. 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 earning announcement is disclosed overnight on date t, we consider the opening price on date $t + 1$. Table II displays the results. For positive news, the average return is greater than 47% and the median return is greater than 36%. These values are remarkable given than the median time interval from a trade to the private information disclosure is seven days. To put these returns in perspective, we compute the same returns for the sample of SEC form 13D filers between 1994 and 2011. 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 4.7% and 2.2%, respectively.

5 Evidence from Illegal Insider Trading

5.1 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 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 a set of four following measures–*IV*, *PR*, *OS*, and *ES*–in the event window, along with the two standard errors bounds around the mean. Panel A of Figure 2 shows the results for the unrestricted event window. The results indicate that some measures indeed get elevated prior to event date, which might bias downward the magnitude of our results. This is especially true for *IV*, *PR*, and *ES* and less so for *OS*. 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.[18] We show the construction of the event window in the figure below.

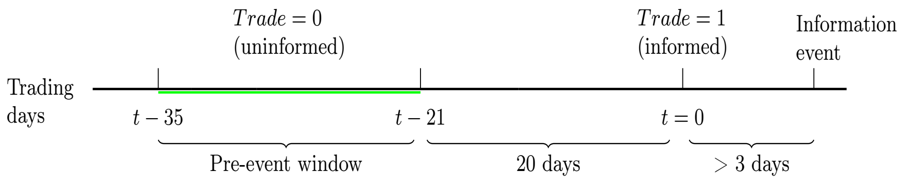

Figure 1. Event Study Time Line

To evaluate the quality of the alternative event window specification, we report in Panel B of Figure 2 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:

$$IM_{it} = a + b \times TRADE_i + c \times Controls_{it} + \mathrm{d}_i + \mathrm{e}_t + \mathrm{error}_{it}. \quad (3)$$

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

[18] 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.

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.[19] 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 V 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 5.4, 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-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

[19] 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 5.3.

equivalent to estimating a regression model in (3) except that we replace IM with $CAIM$.

$$CAIM_{it} = a + b\times\text{TRADE}_{it,t-k} + c\times\text{Controls}_{it} + \text{d}_i + \text{e}_t + \text{error}_{it}. \quad (4)$$

5.2 Baseline Results

In Table VII, 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, only two (*Lambda* and *DI*) are statistically significantly different on event days, at the 5% and 10% levels of statistical significance, respectively. Notably, both coefficients are negative, which suggests that liquidity is generally higher on the informed trading day. The remaining seven coefficients do not show any abnormal behavior on the event days. 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. At the same time, the effect on *DI* becomes larger and is significant at the 1% level. Also, *PR* becomes significant at the 10% level. 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 *PR* and *DI* retain their economic and statistical significance. In that specification, *QS* is statistically significant at the 10% level. 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, $CAIM$. Again, the only significant coefficients are those of *PR* and *DI*, both significant at the 1% level. Also, the magnitudes of the 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 VIII 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 particular, across all four specifications we find that six out of nine measures have significant coefficients of $TRADE$. We observe the most consistent patterns for measures that rely on the mix of options and stock volume: $VR_{o|s}$, $VR_{x|s}$, $VR_{p|s}$, and VR_{otm}. The pure volume based measure

VR_{otm} does not correlate strongly with $TRADE$. Of the measures based on option prices QS_o and IV_o show the most robust behavior.

Overall, our results indicate that option-based 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 even though almost all of them have the ability to predict future returns.

5.3 Discussion of 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 results do not support this view.

First, almost all stock-based measures fail to reveal private information. This is the case even when we restrict our sample to trades with high insider trading volume. 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, we find that certain option measures detect information even when no option trading was done by insiders, the result we report in Table XIV.

Arguably, the SEC is unlikely to rely on public, information-based liquidity or volatility measures to detect illegal activity in the first place. Instead, an important source of investigation is the whistleblowing program, through which whistleblowers are compensated for reporting illegal activities directly to the SEC or related agencies. Indeed, based on a sample of cases filed by the SEC in the eighties, before the implementation of the formal whistleblower program, Meulbroek (1992) reports that "public complaints", a category of investigations initiated for reasons unrelated to insider trading, 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.

To further address the possibility of selection bias, we perform two following tests. First, we follow Meulbroek (1992) and compare the response of information measures on insider trading days across two subsamples: The set of single-firm investigations and the set of multiple-firm investigations. The idea behind this test is that the probability of selection bias is greater for single-firm cases than it is for multiple-firm 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. The results are reported in Table XI.

In Panels A and B, we report the results for stock-based measures. Even though the results for DI and QS are less significant for the multiple-firm cases, the magnitudes are not statistically different from each other. Further, the results for PR are in fact stronger for cases with multiple firms. Similarly, in Panels C and D we report the results for option-based measures. The results for these measures are generally stronger for multiple-firm cases. In particular, the price-based measures of QS_o and IV become significant for the multiple-firm sample. Overall, it is unlikely that our results are driven by the selection of cases based on information measures.

Second, we split our 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 3. 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.

5.4 Exploring the Economic Mechanism

Strategic Incentives One of the important questions is whether insider traders use their information strategically when they trade. For example, they might trade at times when liquidity in the market is the highest. They can also use limit orders in their strategies. In a recent paper, Collin-Dufresne and Fos (2015) show that large institutional traders tend to trade at times when liquidity is highest and suggest that this might be evidence of strategic trading. This conclusion, however, is hard to verify since it is hard to confirm whether large investors indeed trade using private information and whether they choose an optimal stopping time in their trading decision. The advantage of our data is that we know precisely whether traders utilize their private information and crucially we know the times of information acquisition and its use.

To show whether insiders are strategic in their behavior we propose five empirical tests. All of them aim to study settings in which it is unlikely that the decision to trade is strategic. Our first test is based on the distance between the information acquisition and its use. If traders are strategic, and the information arrival is orthogonal to general market conditions, one would imagine that the time to use information would take at least a few days. Thus any trade that is executed shortly after information arrival is likely non-strategic. We assume that to be the case for any trade executed within 2 days after information arrival. Our second test uses the idea that strategic traders are likely to have more experience and thus trade more. To this end, we define traders to be non-strategic if they trade less than 8 times during the entire sample period, where the cutoff point is the median value of the number of trades among all traders.

Our third test assumes that traders are less likely to act strategically if they trade a given company less actively. The cutoff point defined based on the median value of trades is 5. Hence, traders with fewer than 6 trades are less strategic. In our fourth test, we define strategic trade based on the number of total trades for a given legal case. The idea is that if there are many trades within a given case this might be indicative of more concerted or strategic behavior of all traders. The cutoff point for the non-strategic behavior is number of trades per case not more than 15. Finally, in our last test, we consider cases in which an insider is likely less sophisticated and thus less likely to trade strategically. We define unsophisticated traders as those whose profits from trading are less than $100,000.

We present the results from the tests for stock-based measures in Panels A-E of Table XII. In all panels, we report the results that mimic the design of Panels B and D in Table VII (with $CAIM$ as the dependent variable). Compared to the results in Panel B of Table VII, we find that the relationship between information measures and event date weakens for DI but the results are still negative and statistically significant. The coefficient is now significant at the 5% level of significance in two cases and at the 10% level in the remaining three cases. This suggests that although part of the correlation between $TRADE$ and DI could be a reflection of the strategic behavior of traders some of this effect is unlikely driven by the strategic trading motives. The same is true for PR which is now insignificant. In turn, *Lambda* is significant in Panels A and C, and PI and RV are significant in Panels D and E.

Similarly, we compare the results for option-based measures in Table **??** with those in Panel D of Table VII. Our main finding is that all the previously significant coefficients for price-based measures (QS_o and IV) lose their significance. At the same time, the measures based on option and stock volume retain their significance, though in some cases the significance gets weaker. These results suggest that measures based on prices are more likely to reflect strategic motives for trade, while the measures based on volume detect non-strategic trading. Overall, these results indicate that popular measures of informed trading reflect a significant non-strategic component of trading.

Information Spillovers One possibility is that measures of information correlate with event date simply because the traders' actions are large enough to affect the values of measures. For example, a large volume of options traded by insider could significantly affect the $VR_{o|s}$ measure. Likewise, a large block of stock trading by the insider could affect the value of DI. While these direct relationships are part of the essence of empirical design, another interesting possibility is that the trade executed by insiders in one market affects the value of information measures based on information in another market. For example, a large trade in option market could spill over to an equity market simply because market makers setting quotes in option markets could also set quotes in stock markets as well. Alternatively, traders observing unusual activity in option markets could infer the possibility of insider trading and accordingly trade on this information in equity markets.

In this section, we evaluate the presence of the direct and indirect cross-market linkages by looking at the correlation of information measures with the event day conditional on the type of instrument that is being used by an insider trader. In our first test, we estimate our regression models for the sample of insider trades that were executed in the stock market. If the direct influence mechanism is at play we should expect the stock-based measures to be correlated with $TRADE$. In turn, if the indirect channel matters we should expect that the option-based measures be also correlated with $TRADE$.

We report the results for stock-based measures in Table XIII. The results for stocks-only trades in Panels A and B indicate patterns that closely mimic those in Table VII. We find that only two coefficients, those of PR and DI, are statistically significant, which may suggest that the importance of the direct channel in the stock markets. The results for options-only trades in Panels C and D are significantly weaker, both in terms of magnitudes and statistical significance, which suggests no spillover effects from options to equity markets.

Similarly, in Table XIV we report the results for option-based measures. In Panels A and B, we present the results for options-only trades. We find a strong relationship between information measures and event day for seven measures. The effect is insignificant for VR_{otm}. These results support the direct channel effect. In Panels C and D, we show the results for stocks-only trades. Unlike for the stock-based measures, we find that the significance of options measures does not deteriorate much. Again, seven measures are statistically significant, with the exception of IVS and VR_{otm}. These results suggest that option markets reflect the private information that is injected in the stock market.

Overall, we find strong evidence of both direct and indirect transmission channel for the option-based measures and some evidence of direct transmission and not much of indirect transmission for the stock-based measures.

5.5 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. We also provide additional evidence from signed-quote options markets.

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. We estimate the regression model with control adjusted information measures as dependent variables. The results are presented in Table XV. The first three panels report results for stock-based measures, while the remaining three panels report the results for the option-based measures.

Evidence for stock-based measures indicates that such measures are only useful for detecting private information in the case of mergers and acquisitions. Similar to our earlier results, 2 out of 9 measures, *PR* and *DI*, are statistically significantly related to trading event. In turn, for earnings announcements only one measure, *PI*, is significant at the 10% level. No measures are significant for other corporate events.

Our findings for option-based measures paint a similar picture in that the most measures can precisely identify private information for mergers and acquisitions. These are price-based measures (QS_o and IV) and volume-based measures ($VR_{o|s}$, $VR_{c|s}$, $VR_{p|s}$, and $VR_{otm|s}$). A slightly smaller set of 5 variables works well for earnings announcements, and only 2 measures correlate significantly with $TRADE$ in cases of Other Events. Of all the measures, IV and $VR_{otm|s}$ are statistically significant predictors of information in all three categories of events.

In sum, we find that across all categories of corporate events, information measures best identify information in cases of mergers and acquisitions and earnings announcements. They do not do a good job for general corporate events. Given that our measures of information seem to work best for mergers and acquisitions which are more difficult to time by regular traders because 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 controls-adjusted information measures. We report the results in Table XVI for stock-based measures (Panels A and B) and option-based measures (Panels C and D).

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, seven out of nine measures are statistically significant for option-based measures. The coefficients become significantly weaker for the sample of negative news. Only QS is statistically significant among stock-based measures. In the sample of option-based measures the coefficients are only marginally significant for two measures ($VR_{o|s}$and $VR_{c|s}$) and statistically significant at the 5% level for VR_{otm}. One reason behind the apparent disparity in quality across news types is that some information measures are largely bets on positive news. This is especially true for call-based measures.

Conditioning on the exchange venue Companies traded by insiders are listed on different exchanges. To the extent that the provision of liquidity and the attention of investors might vary across this dimension, it might be relevant to evaluate whether the listing of a company's stock affects the quality of the underlying information measure. In particular, we consider three different possibilities: NYSE, Nasdaq, and all other exchanges. The highest percentage of companies are listed on Nasdaq, followed by NYSE, and other exchanges. We estimate the regression models with controls-adjusted information measures. We report the results in Table **??** for stock-based measures (Panels A-C) and for option-based measures (Panels D-F).

The results indicate that stock-based measures' ability to capture insider trades varies across listing exchanges. In particular, PR and RV are statistically significant for companies listed on NYSE. DI is significant for companies listed on Nasdaq, while *Lambda* is significant for companies listed on other exchanges. Similarly, option-based measures perform best for companies listed on NYSE or Nasdaq. Across the two exchanges IV, $VR_{o|s}$, $VR_{c|s}$, and VR_{los} are significantly related to $TRADE$. Notably, none of the option-based measures is significant for other exchanges, but the caveat is the number of observations in this bin is particularly small possibly because companies listed on smaller exchanges do not have actively traded option contracts. Overall, we observe a significant variation across listing exchanges in the ability to capture insider trades with Nasdaq-listed companies having the best hit ratio.

Evidence from signed options data The results in the paper highlight that option-based measures are better able to capture informed trades. In particular, measures that combine option and stock volume perform well. 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 Vol OS 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).

6 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 expolit legal investigations to reconstruct precisely-identified information flows and its 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 much less studied in the literature, are desirable in this regard. Remarkably, 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 trade 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 might call for more effort to include volume. This 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. We also show that private information spills over across different markets (in our case from equity to options market), a result consistent with a theoretical model of correlated market making of Cespa and Foucault (2014).

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)

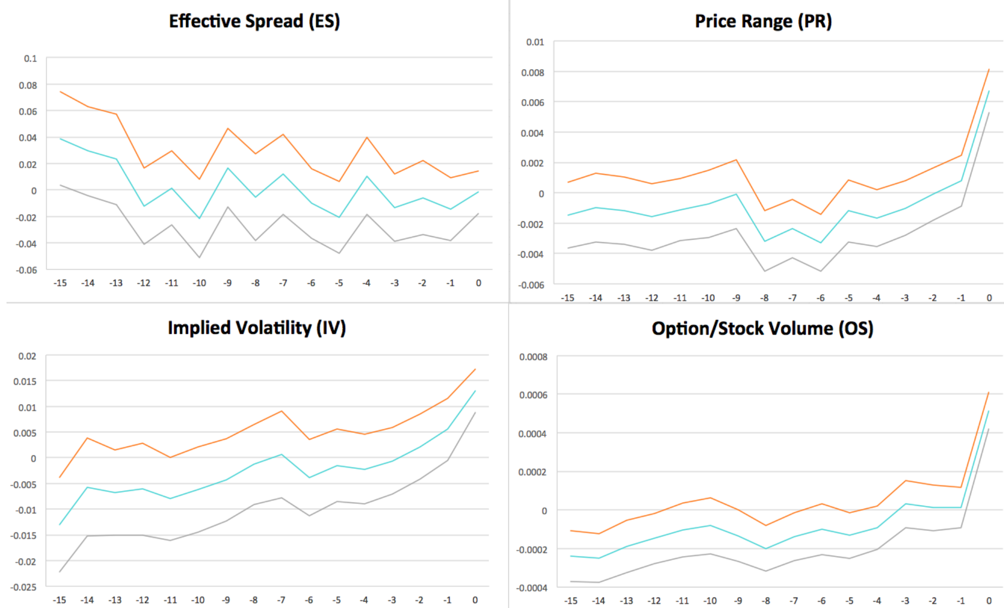
- QS: Quoted bid–ask spread for stocks (TAQ NBBO) as a percent of the midquote. Time weighted daily average.
- PI: Price impact for stocks (NBBO). Five-minutes midquote change. Dollar-weighted daily average. Lee-Ready trade sign classification.
- PR: Price range, defined as the maximum daily ask price 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.

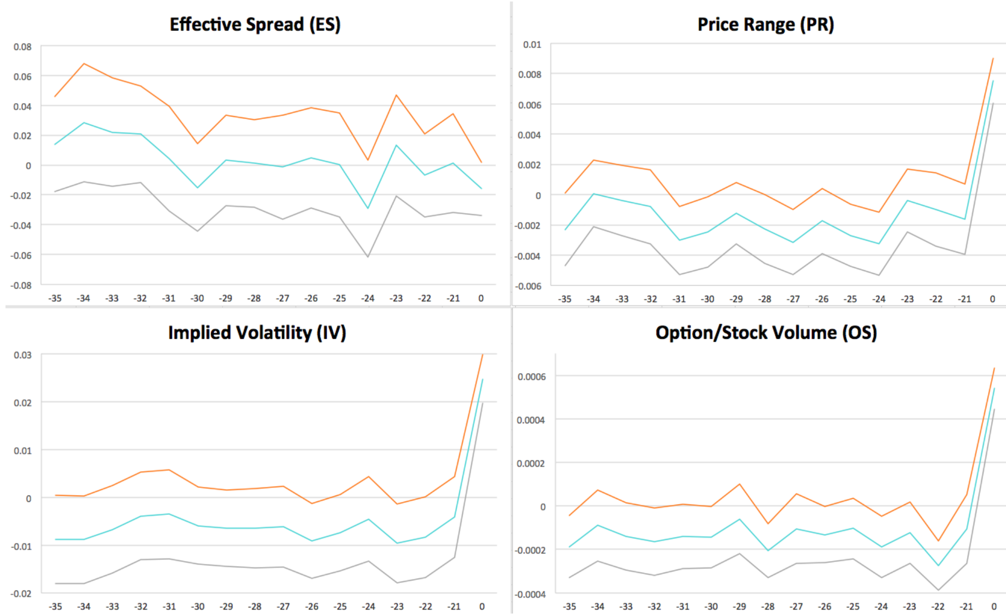
- QS_o: Daily arithmetic average of quoted bid–ask spread for all traded options on the same underlying.
- IV_o: Daily arithmetic average of OMIV for all traded options on the same underlying.
- IVS: Implied volatility spread, given by the average difference in OMIV between call and put options with 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. Information Measures in the Pre-Event Window

Panel A: Short Pre-event Window

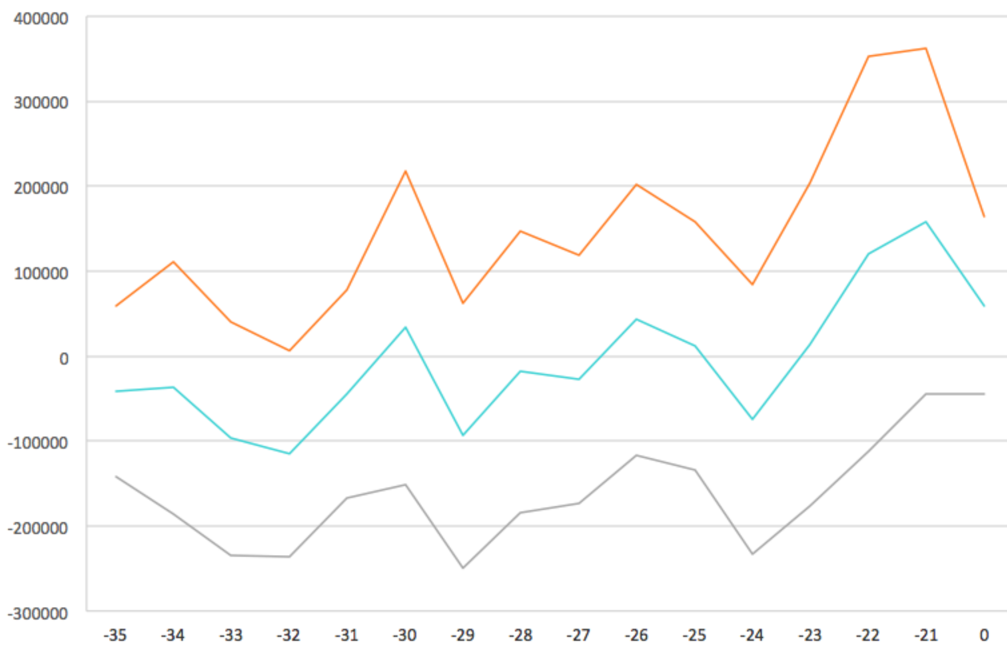


Panel B: Extended Pre-event Window



The figure presents the average values (aggregated across all trades) along with their 2-standard error bounds of four information measures. Time 0 denotes the time of insider trade. Figure 2a considers [-1,-15] trading days as the pre-event window. Figure 2b considers [-21,-35] trading days as the pre-event window and excludes events in which insider trading happens within three trading days of the information event. All measures are adjusted for firm and time fixed effects. The detailed definitions of information measures are provided in Section 2.

Figure 3. 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.

Table III
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 1995-2012. **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	0.554	0.200	0.882
PI_s	10.723	4.592	18.040
PR_s	4.781	3.608	3.963
RV_s	0.105	0.048	0.149
AOI_s	0.153	0.110	0.149
$Lambda_s$	0.150	0.022	0.327
DI_s	0.462	0.036	1.736
Panel B: Option-based measures			
QS_o	0.563	0.469	0.360
QS_{otm}	0.835	0.736	0.475
IV_c	0.553	0.483	0.268
IV_p	0.592	0.507	0.285
IVS	-0.010	-0.007	0.052
AV_o	102.27	-31.45	6715.79
VR_{otm}	29.241	2.273	43.441
DI_o	0.134	0.005	0.560
Panel C: Mixed measures			
$QSR_{o\|s}$	607.41	339.44	829.21
$VR_{o\|s}$	0.132	0.052	0.223
$VR_{c\|s}$	0.084	0.031	0.146
$VR_{p\|s}$	0.047	0.011	0.100
$DI_{s\|o}$	0.458	0.029	1.767
$DI_{o\|s}$	0.210	0.037	0.628
Panel D: Control variables			
$LNSIZE$	13.499	13.334	1.999
$LNVOL$	12.677	12.854	2.308
$TURNOVER$	0.0123	0.008	0.013
PRC	23.970	17.562	22.011

Table IV
Descriptive Statistics: Legal Cases Characteristics

The unit of observation is legal insider trading case. **In Panel A**, we provide the distribution of cases with respect to the event type. **In Panel B**, we classify cases by year of filing. **In Panel C**, we show the distribution of the number of firms involved in a given legal case.

Distribution of Insider Events	Number of Cases	Percentage of Cases
Panel A: By event type		
Mergers & Acquisitions	209	56.49
Earnings Announcements	70	18.92
General Business Events	43	11.62
Other Corporate Events	21	5.68
Shares Offerings & Tendering	18	4.86
Other News	7	1.89
No information	2	0.54
Total	370	100
Panel B: By Year		
2001	16	4.32
2002	33	8.92
2003	31	8.38
2004	23	6.22
2005	32	8.65
2006	30	8.11
2007	33	8.92
2008	37	10
2009	25	6.76
2010	29	7.84
2011	35	9.46
2012	46	12.43
Panel C: Number of Firms per Case		
1	295	79.73
2	27	7.30
3	11	2.97
4	8	2.16
5	6	1.62
6	5	1.35
7	3	0.81
9	1	0.27
10	4	1.08
11	1	0.27
12	1	0.27
13	1	0.27
15	1	0.27
19	1	0.27
20	2	0.54
24	2	0.54
25	1	0.54

Table V
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 classify trades by the primary listing venue of the company's equity shares. **In Panel D**, we show the distribution of trades by year. **In Panel** E, we show the distribution of trades by month. **In Panel F**, we show the distribution of insider trades with respect to the traded company's primary 2-digit SIC code.

Panel A: Distribution of Trading Instruments	**Number of trades**	**Percentage of trades**
Stocks	2,554	71.22
Options	997	27.82
ADS	23	0.65
Bonds	12	0.33
Total	3,586	100
Panel B: Distribution of Buys and Sells		
Buys	3,020	83.34
Sales	566	16.66
Panel C: Trades and Trading Venue		
NASDAQ	2,010	62.58
NYSE	1,043	32.47
AMEX	147	4.58
Other	10	0.31
Arca	2	0.06
Panel D: Distribution of Trades by Year		
1995	17	0.48
1996	2	0.06
1997	17	0.48
1998	57	1.62
1999	103	2.93
2000	252	7.17
2001	180	5.12
2002	206	5.86
2003	205	5.83
2004	208	5.91
2005	215	6.11
2006	347	9.87
2007	600	17.06
2008	427	12.14
2009	327	9.3
2010	191	5.43
2011	98	2.79
2012	65	1.85

Table V (Continued)

Descriptive Statistics: Trade Characteristics (continued)

Panel E: Distribution of Trades by Month

Month	**Number of Trades**	**Percentage of all trades**
January	281	7.99
February	257	7.31
March	316	8.99
April	343	9.76
May	290	8.25
June	342	9.73
July	381	10.84
August	274	7.79
September	294	8.36
October	242	6.88
November	237	6.74
December	259	7.37

Panel F: Distribution of trades by SIC2 Industry Code

	SIC2 Code	**Number of Trades**	**Percent of trades**
Chemicals	28	581	18.09
Business Services	73	486	15.13
Electronic Equipment	36	276	8.59
Measuring and Controlling Equipment	38	239	7.44
Depositary Institutions	60	153	4.76
Industrial and Commercial Machinery	35	150	4.67
Wholesale Trade: Durable Goods	50	98	3.05
Oil and Gas Extraction	13	84	2.62
Food	20	72	2.24
Miscellaneous Retail Trade	59	69	2.15
Other Industries	-	1,004	31.26

Panel G: Trading Statistics

Characteristic	mean	median	st. dev.	min	max
Distance from news to trade	7.88	1	19	0	266
Trades per trader	13.73	7	16.27	1	73
Trades per firm	23.89	13	35.06	1	171
Firms per case	4.88	2	6.29	1	25
Distance from trade to event	28.28	7	73.34	0	998
Trader age	45.28	44	11.51	22	82
Tipper age	44.18	43	11.34	23	78
Trader gender (male in %)	93.74	-	-	-	-
Tipper gender (male in %)	92.73	-	-	-	-
Trader sophistication	0.49	-	-	-	-
Reported profit ($1,000s)	831.1	93.55	4151.3	8.5	12500

Table VI
Information Measures Around Earnings Announcements

The dependent variables are information measures. All definitions of control variables, measured at the daily frequency, mirror those in Table III. 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: Within 3 days before announcement							
TRADE	0.001	0.179**	0.440***	0.002	-0.000	-0.000	-0.037***
	(0.004)	(0.080)	(0.024)	(0.001)	(0.001)	(0.002)	(0.009)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	55,544	55,530	262,903	12,993	55,531	12,993	260,573
	QS_o	QS_{otm}	IV_c	IV_p	IVS	VR_{otm}	DI_o
Panel B: Option-based measures: Within 3 days before announcement							
TRADE	-0.016***	-0.025***	0.017***	0.018***	0.000	-3.047***	-0.029***
	(0.004)	(0.007)	(0.002)	(0.002)	(0.000)	(0.351)	(0.005)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	135,970	135,970	135,274	133,938	138,024	138,024	122,938
	$QSR_{o\|s}$	$VR_{o\|s}$	$VR_{c\|s}$	$VR_{p\|s}$	$DI_{s\|o}$	$DI_{o\|s}$	
Panel C: Stock- and Option-based measures: Within 3 days before announcement							
TRADE	-39.212***	0.028***	0.016***	0.012***	-0.082***	-0.005	
	(6.785)	(0.003)	(0.002)	(0.001)	(0.013)	(0.004)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	
#Obs	130,432	138,024	138,022	138,022	124,069	134,933	

Table VI (Continued)

Information Measures Around Earnings Announcements

	QS_s	PI_s	PR_s	RV_s	AOI_s	$Lambda_s$	DI_s
Panel D: Stock-based measures: Within 4-10 days before announcement							
TRADE	0.006*	-0.003	-0.037***	-0.000	0.000	-0.001	-0.003
	(0.003)	(0.067)	(0.013)	(0.001)	(0.001)	(0.001)	(0.006)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	67,402	67,389	319,056	15,690	67,389	15,690	316,160
	QS_o	QS_{otm}	IV_c	IV_p	IVS	VR_{otm}	DI_o
Panel E: Option-based measures: Within 4-10 days before announcement							
TRADE	-0.005**	-0.007*	0.005***	0.005***	0.000	-0.079	-0.007**
	(0.002)	(0.004)	(0.001)	(0.001)	(0.000)	(0.212)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	164,978	164,978	164,152	162,508	167,471	167,471	148,169
	$QSR_{o\|s}$	$VR_{o\|s}$	$VR_{c\|s}$	$VR_{p\|s}$	$DI_{s\|o}$	$DI_{o\|s}$	
Panel F: Stock- and Option-based measures: Within 4-10 days before announcement							
TRADE	-2.778	0.001	0.001	0.000	-0.007	0.001	
	(4.199)	(0.001)	(0.001)	(0.000)	(0.010)	(0.003)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	
#Obs	158,306	167,471	167,466	167,466	149,448	163,769	

Table VII
Stock-based Measures: Baseline Specification

The dependent variables are stock-based information measures, measured at the company level at time t over the period 1995-2012. *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 III. **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	-0.097***	-0.205	0.801***	0.022***	-0.011**	-0.031***	-0.193***
	(0.029)	(0.498)	(0.162)	(0.006)	(0.005)	(0.010)	(0.055)
LNSIZE	-0.202***	-3.326***	-0.985***	-0.032***	-0.017***	-0.128***	0.076
	(0.052)	(0.651)	(0.233)	(0.010)	(0.006)	(0.017)	(0.090)
LNVOL	-0.031	-0.320	0.545***	0.014**	-0.015**	0.046***	-0.425***
	(0.046)	(0.515)	(0.126)	(0.006)	(0.007)	(0.013)	(0.095)
TURNOVER	-4.673	-195.970***	28.828*	1.117	-0.277	-8.618***	17.242**
	(4.223)	(57.177)	(16.066)	(0.711)	(0.518)	(1.525)	(7.144)
PRC	-0.000	-0.018	-0.013	-0.001	-0.000	0.001	-0.005
	(0.002)	(0.031)	(0.014)	(0.001)	(0.000)	(0.001)	(0.004)
Constant	0.418***	8.218***	4.442***	0.092***	0.134***	0.107***	0.267***
	(0.028)	(0.392)	(0.164)	(0.007)	(0.003)	(0.010)	(0.036)
#Obs	10,072	10,068	10,498	9,597	10,068	9,597	10,427
Panel B: With firm fixed effects							
TRADE	-0.063***	0.384	0.885***	0.027***	-0.007	-0.009	-0.191***
	(0.021)	(0.476)	(0.157)	(0.007)	(0.004)	(0.008)	(0.054)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	10,072	10,068	10,498	9,597	10,068	9,597	10,427
Panel C: With time and firm fixed effects							
TRADE	-0.063***	0.243	0.897***	0.025***	-0.007*	-0.003	-0.187***
	(0.021)	(0.448)	(0.148)	(0.006)	(0.004)	(0.008)	(0.053)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	10,072	10,068	10,498	9,597	10,068	9,597	10,427
Panel D: With time and firm fixed effects (control group adjusted)							
TRADE	-0.012	0.084	0.884***	0.001	0.001	-0.001	-0.186***
	(0.014)	(0.285)	(0.143)	(0.002)	(0.002)	(0.003)	(0.053)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	10,072	10,068	10,498	9,597	10,068	9,597	10,427

Table VIII
Option-based Measures: Baseline Specification

The dependent variables are option-based information measures, measured at the company level at time t over the period 1995-2012. *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 III. **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	-0.026	-0.063**	0.042***	0.032**	0.004	1,336.474***	-3.405	-0.087***
	(0.023)	(0.029)	(0.015)	(0.016)	(0.003)	(447.247)	(2.071)	(0.021)
LNSIZE	-0.074**	-0.084**	-0.120**	-0.113*	-0.003	148.245	-4.961**	0.034
	(0.035)	(0.041)	(0.053)	(0.060)	(0.004)	(129.690)	(2.482)	(0.030)
LNVOL	-0.006	-0.028	0.092**	0.086*	0.003	-171.773	-4.704*	-0.103***
	(0.037)	(0.043)	(0.042)	(0.049)	(0.004)	(224.004)	(2.623)	(0.034)
TURNOVER	-4.403	-4.062	-0.611	0.348	-0.625	16,748.511	-382.863**	0.773
	(2.851)	(3.138)	(3.452)	(3.970)	(0.401)	(19,101.159)	(191.800)	(1.991)
PRC	-0.001	-0.001	-0.001	-0.001	0.000	-12.537	-0.179*	-0.002**
	(0.001)	(0.002)	(0.002)	(0.003)	(0.000)	(10.329)	(0.097)	(0.001)
Constant	0.572***	0.847***	0.549***	0.592***	-0.011***	-163.832	30.141***	0.167***
	(0.018)	(0.022)	(0.018)	(0.020)	(0.002)	(101.088)	(1.395)	(0.018)
#Obs	7,191	7,191	7,058	6,986	7,236	7,228	7,236	6,486
Panel B: With firm fixed effects								
TRADE	-0.010	-0.045	0.038***	0.026***	0.004	1,361.988***	-2.110	-0.084***
	(0.022)	(0.028)	(0.009)	(0.010)	(0.003)	(462.885)	(2.164)	(0.021)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	7,191	7,191	7,058	6,986	7,236	7,228	7,236	6,486
Panel C: With time and firm fixed effects								
TRADE	-0.017	-0.052**	0.036***	0.024***	0.004	1,266.361***	-2.545	-0.084***
	(0.019)	(0.025)	(0.008)	(0.009)	(0.003)	(411.539)	(2.144)	(0.021)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	7,191	7,191	7,058	6,986	7,236	7,228	7,236	6,486
Panel D: With time and firm fixed effects (control group adjusted)								
TRADE	-0.025	-0.058**	0.037***	0.027***	0.004	n/a	-2.722	-0.061***
	(0.018)	(0.024)	(0.009)	(0.009)	(0.003)	n/a	(1.962)	(0.020)
Controls	Yes	Yes	Yes	Yes	Yes	n/a	Yes	Yes
#Obs	7,191	7,191	7,058	6,986	7,236	n/a	7,236	6,486

Table IX
Stock- and Option-based Measures: Baseline Specification

The dependent variables are option-based information measures, measured at the company level at time t over the period 1995-2012. *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 III. **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	-49.095	0.068***	0.055***	0.010**	-0.230***	-0.063***
	(32.842)	(0.012)	(0.009)	(0.004)	(0.060)	(0.023)
LNSIZE	215.666***	-0.017	-0.007	-0.009	-0.172*	0.048
	(71.379)	(0.016)	(0.009)	(0.007)	(0.097)	(0.039)
LNVOL	-264.755***	0.023	0.010	0.013*	-0.049	-0.176***
	(76.128)	(0.016)	(0.009)	(0.007)	(0.102)	(0.045)
TURNOVER	16,027.952***	-1.102	-0.472	-0.550	-11.713	4.233*
	(5,329.090)	(1.360)	(0.805)	(0.627)	(7.210)	(2.512)
PRC	4.348	0.003***	0.002**	0.002***	-0.002	-0.003**
	(4.106)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)
Constant	636.743***	0.114***	0.070***	0.043***	0.555***	0.232***
	(37.219)	(0.008)	(0.005)	(0.004)	(0.050)	(0.025)
#Obs	6,932	7,236	7,235	7,236	6,575	7,031
Panel B: With firm fixed effects						
TRADE	-24.314	0.068***	0.053***	0.012***	-0.208***	-0.071**
	(33.700)	(0.011)	(0.008)	(0.004)	(0.063)	(0.031)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	6,932	7,236	7,235	7,236	6,575	7,031
Panel C: With time and firm fixed effects						
TRADE	-37.472	0.069***	0.053***	0.012***	-0.215***	-0.067**
	(32.857)	(0.011)	(0.008)	(0.004)	(0.063)	(0.031)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	6,932	7,236	7,235	7,236	6,575	7,031
Panel D: With time and firm fixed effects (control group adjusted)						
TRADE	-32.363	0.064***	0.049***	0.011***	-0.172***	-0.061**
	(31.913)	(0.011)	(0.008)	(0.004)	(0.057)	(0.028)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	6,932	7,236	7,235	7,236	6,575	7,031

Table X
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 1995-2012. *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 III. **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	30-60d	>60d	ITM	ATM	OTM
Panel A: $VR_{o\|s}$ **with time and firm fixed effects**							
TRADE	0.007**	0.026***	0.025***	0.004	0.006***	0.008**	0.049***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.002)	(0.003)	(0.008)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	7,236	7,236	7,236	7,236	7,236	7,236	7,236
Panel B: $VR_{o\|s}$ **with time and firm fixed effects (control group adjusted)**							
TRADE	0.007**	0.025***	0.024***	0.003	0.006***	0.008**	0.046***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.002)	(0.003)	(0.007)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	7,236	7,236	7,236	7,236	7,236	7,236	7,236

Table XI
Number of Firms Per Case

The dependent variables are stock-based information measures (**in Panels A and B**) and option-based information measures (**in Panels C and D**), measured at the company level at time t over the period 1995-2012. *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 III. **In Panels A and C**, we consider trades related to legal cases with one firm being traded; **in Panels B and D**, we consider legal cases that involve more than one firm. 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: One firm							
TRADE	-0.012	0.624**	0.739***	-0.004	0.002	-0.001	-0.226**
	(0.017)	(0.313)	(0.215)	(0.003)	(0.002)	(0.002)	(0.095)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	4,609	4,605	4,785	4,434	4,605	4,434	4,730
Panel B: Stock-based measures: Two or more firms							
TRADE	-0.020	-0.573	0.962***	0.006*	0.000	-0.002	-0.154***
	(0.022)	(0.466)	(0.185)	(0.003)	(0.004)	(0.005)	(0.052)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	5,291	5,291	5,405	5,056	5,291	5,056	5,389

	QS_o	QS_{otm}	IV_c	IV_p	IVS	VR_{otm}	DI_o
Panel C: Option-based measures: Single firm							
TRADE	0.020	-0.009	0.027**	0.013	0.006	-2.357	-0.061*
	(0.026)	(0.036)	(0.011)	(0.011)	(0.005)	(2.503)	(0.032)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	3,356	3,356	3,283	3,283	3,356	3,356	3,004
Panel D: Option-based measures: Two or more firms							
TRADE	-0.052**	-0.083***	0.042***	0.038**	0.002	-2.759	-0.053**
	(0.024)	(0.032)	(0.014)	(0.016)	(0.003)	(2.889)	(0.025)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	3,709	3,709	3,658	3,592	3,754	3,754	3,387

Table XII
Stock-based Measures: Non-Strategic Incentives

The dependent variables are stock-based information measures, measured at the company level at time t over the period 1995-2012. *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 III. **In Panel A**, we consider all trades that happen within two trading days of the information acquisition. **In Panel B**, we include trades of traders with below median value of all trades (equal to 7). **In Panel C**, we include trades of companies with below median value of trades (equal to 5). **In Panel D**, we include trades that come from legal cases with below median value of trades (equal to 15). **In Panel E** we only include trades with profits less than $100k. All regressions include time and firm fixed affects. 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.

	QS_s	QS_o	DI_s	DI_o	DI_{so}	DI_{os}
Panel A: Trade within two days of information acquisition						
TRADE	0.010	0.026	-0.136**	-0.140**	-0.368***	-0.007
	(0.024)	(0.037)	(0.064)	(0.056)	(0.114)	(0.066)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	2,888	2,077	2,916	1,907	1,918	2,082
Panel B: Number of same-trader trades less than or equal to 7						
TRADE	-0.009	-0.032	-0.170***	-0.073***	-0.149*	-0.109**
	(0.015)	(0.029)	(0.056)	(0.025)	(0.076)	(0.042)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	4,876	3,311	5,015	2,971	3,004	3,235
Panel C: Number of trades per company less than or equal to 5						
TRADE	-0.040**	-0.024	-0.143***	-0.072*	-0.106	-0.023
	(0.020)	(0.025)	(0.045)	(0.040)	(0.093)	(0.047)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	4,904	2,933	4,971	2,597	2,627	2,840
Panel D: Number of trades per legal case less than 15						
TRADE	-0.019	-0.026	-0.275**	-0.085**	-0.191*	-0.063**
	(0.018)	(0.023)	(0.109)	(0.034)	(0.111)	(0.030)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	4,651	3,130	4,790	2,777	2,799	3,051
Panel E: Profits lower than $100k						
TRADE	-0.002	-0.041	-0.219***	-0.080**	-0.266***	-0.074
	(0.021)	(0.028)	(0.079)	(0.036)	(0.097)	(0.048)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	5,399	3,468	5,537	3,130	3,177	3,425

Table XIII
Evidence from Types of Trades: Stock-based Measures

The dependent variables are stock-based information measures, measured at the company level at time t over the period 1995-2012. *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 III. **In Panels A and B**, we only include trades in stocks. **In Panels C and D**, we only include trades in options. Panels A and C include firm and time fixed effects while Panels B and D 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	RV_s	PR_s	$Lambda_s$	DI_s	AOI_s
Panel A: Stocks-only trades with time and firm fixed effects							
TRADE	-0.047*	-0.001	0.006	0.003**	-0.003	-0.458***	0.001
	(0.025)	(0.006)	(0.005)	(0.001)	(0.003)	(0.157)	(0.005)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	6,122	6,118	5,889	6,299	6,122	6,249	6,118
Panel B: Stocks-only trades with time and firm fixed effects (control group adjusted)							
TRADE	-0.007	0.001	-0.003	0.003**	-0.002	-0.433***	0.003
	(0.013)	(0.003)	(0.002)	(0.001)	(0.002)	(0.152)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	6,122	6,118	5,889	6,299	6,122	6,249	6,118
Panel C: Options-only trades with time and firm fixed effects							
TRADE	-0.009	0.012**	0.004	0.001	-0.001	-0.027**	-0.003
	(0.009)	(0.005)	(0.003)	(0.001)	(0.001)	(0.013)	(0.005)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	2,434	2,434	2,386	2,451	2,434	2,451	2,434
Panel D: Options-only trades with time and firm fixed effects (control group adjusted)							
TRADE	-0.006	0.004	-0.001	0.001	-0.000	-0.015	0.002
	(0.008)	(0.004)	(0.002)	(0.001)	(0.001)	(0.012)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	2,434	2,434	2,386	2,451	2,434	2,451	2,434

Table XIV
Evidence from Types of Trades: Option-based Measures

The dependent variables are option-based information measures, measured at the company level at time t over the period 1995-2012. *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 III. **In Panels A and B**, we only include trades in options. **In Panels C and D**, we only include trades in stocks. Panels A and C include firm and time fixed effects while Panels B and D 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_o	IV_o	IVS	VR_{otm}	$VR_{o\|s}$	$VR_{c\|s}$	$VR_{p\|s}$	$VR_{otm\|s}$
Panel A: Options-only trades with time and firm fixed effects								
TRADE	-0.040***	0.016***	0.005**	0.805	0.001***	0.001***	0.000***	0.001***
	(0.013)	(0.006)	(0.003)	(3.043)	(0.000)	(0.000)	(0.000)	(0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	2,344	2,344	2,344	2,344	2,344	2,344	2,344	2,344
Panel B: Options-only trades with time and firm fixed effects (control group adjusted)								
TRADE	-0.035***	0.020***	0.007**	-0.111	0.001***	0.001***	0.000***	0.001***
	(0.013)	(0.006)	(0.003)	(2.952)	(0.000)	(0.000)	(0.000)	(0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	2,344	2,344	2,344	2,344	2,344	2,344	2,344	2,344
Panel C: Stocks-only trades with time and firm fixed effects								
TRADE	-0.025**	0.016**	0.001	-0.076	0.001***	0.000***	0.000***	0.000***
	(0.011)	(0.008)	(0.003)	(2.441)	(0.000)	(0.000)	(0.000)	(0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	4,248	4,166	4,248	4,248	4,248	4,247	4,248	4,248
Panel D: Stocks-only trades with time and firm fixed effects (control group adjusted)								
TRADE	-0.021**	0.020**	0.001	-0.705	0.001***	0.000***	0.000**	0.000***
	(0.010)	(0.008)	(0.003)	(2.327)	(0.000)	(0.000)	(0.000)	(0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	4,248	4,166	4,248	4,248	4,248	4,247	4,248	4,248

Table XV

Conditioning on Event Type

The dependent variables are stock-based information measures. This table presents separate results for mergers and acquisitions and earnings announcements. The dependent variables are stock-based information measures.This table presents separate results for positive and negative information events. **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 III. 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	-0.001	0.006***	0.002	0.004	0.000	-0.231***
	(0.017)	(0.004)	(0.001)	(0.003)	(0.003)	(0.006)	(0.067)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	5,493	5,489	5,657	5,239	5,489	5,239	5,598
Panel B: Stock-based measures: Earnings announcements							
TRADE	-0.003	0.005	0.006	0.002	0.012*	0.003	-0.012
	(0.013)	(0.004)	(0.005)	(0.004)	(0.007)	(0.003)	(0.014)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	1,402	1,402	1,445	1,381	1,402	1,381	1,445
	QS_o	QS_{otm}	IV_c	IV_p	IVS	VR_{otm}	DI_o
Panel C: Option-based measures: Mergers and acquisitions							
TRADE	-0.024	-0.082**	0.034***	0.025*	0.005*	-3.999	-0.095***
	(0.028)	(0.036)	(0.012)	(0.013)	(0.003)	(2.781)	(0.030)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	3,762	3,762	3,728	3,676	3,788	3,788	3,282
Panel D: Option-based measures: Earnings announcements							
TRADE	0.016	0.009	0.017	0.003	-0.002	2.119	-0.034
	(0.028)	(0.038)	(0.014)	(0.014)	(0.004)	(3.807)	(0.023)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	1,282	1,282	1,298	1,298	1,300	1,300	1,269
	$QSR_{o\|s}$	$VR_{o\|s}$	$VR_{c\|s}$	$VR_{p\|s}$	$DI_{s\|o}$	$DI_{o\|s}$	
Panel E: Stock- and Option-based measures: Mergers and acquisitions							
TRADE	-11.606	0.070***	0.059***	0.006	-0.255***	-0.075*	
	(45.900)	(0.016)	(0.013)	(0.005)	(0.085)	(0.045)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	
#Obs	3,645	3,788	3,788	3,788	3,330	3,711	
Panel F: Stock- and Option-based measures: Earnings announcements							
TRADE	6.217	0.044***	0.026**	0.018**	-0.122**	-0.033	
	(74.478)	(0.015)	(0.012)	(0.009)	(0.054)	(0.040)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	
#Obs	1,235	1,300	1,300	1,300	1,272	1,296	

Table XVI
Conditioning on Information Direction

The dependent variables are stock-based information measures.This table presents separate results for positive and negative information events. **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 III. 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	-0.006	-0.001	0.008***	0.005*	0.004	-0.000	-0.198***
	(0.014)	(0.003)	(0.001)	(0.003)	(0.003)	(0.005)	(0.054)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	7,307	7,303	7,507	7,022	7,303	7,022	7,444
Panel B: Stock-based measures: Negative News							
TRADE	-0.050	0.003	0.009**	-0.002	-0.001	-0.001	-0.189
	(0.041)	(0.007)	(0.004)	(0.009)	(0.006)	(0.006)	(0.160)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	2,593	2,593	2,683	2,468	2,593	2,468	2,675
	QS_o	QS_{otm}	IV_c	IV_p	IVS	VR_{otm}	DI_o
Panel C: Option-based measures: Positive News							
TRADE	-0.023	-0.061**	0.043***	0.032***	0.006*	-3.213	-0.069***
	(0.022)	(0.029)	(0.010)	(0.011)	(0.003)	(2.261)	(0.024)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	5,316	5,316	5,198	5,147	5,342	5,342	4,710
Panel D: Option-based measures: Negative News							
TRADE	0.002	-0.004	0.005	0.009	-0.005	-1.055	-0.014
	(0.021)	(0.034)	(0.016)	(0.015)	(0.004)	(3.552)	(0.034)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	1,749	1,749	1,743	1,728	1,768	1,768	1,681
	$QSR_{o\|s}$	$VR_{o\|s}$	$VR_{c\|s}$	$VR_{p\|s}$	$DI_{s\|o}$	$DI_{o\|s}$	
Panel E: Stock- and Option-based measures: Positive News							
TRADE	-17.327	0.069***	0.056***	0.009**	-0.203***	-0.072**	
	(37.106)	(0.014)	(0.010)	(0.004)	(0.067)	(0.036)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	
#Obs	5,118	5,342	5,341	5,342	4,781	5,178	
Panel F: Stock- and Option-based measures: Negative News							
TRADE	26.756	0.030**	0.013	0.017**	-0.073	-0.008	
	(46.720)	(0.012)	(0.008)	(0.008)	(0.076)	(0.015)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	
#Obs	1,690	1,768	1,768	1,768	1,695	1,738	