Chasing Private Information*

Marcin Kacperczyk[†] and Emiliano S. Pagnotta[‡]

February 9, 2016

Abstract

Using a unique 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 weak (strong) signal of private information. Equity market metrics that rely solely on prices or volume fail to be informative while measures that incorporate both are. The most robust metrics combine both option and stock volume. 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 novel guidance in the search for private information.

*The most recent version of this paper can be found [here](#). For helpful comments and conversations we are grateful to Franklin Allen, Yakov Amihud, Harjoat Bhamra, Bruno Biais, Alon Brav, Andrea Buraschi, Lauren Cohen, Diane Del Guercio, Douglas Gale, Joel Hasbrouck, David Hirshleifer, Andrei Kirilenko, Craig Lewis, Lubos Pastor, Krishna Ramaswamy, Gideon Saar, Zheng Sun, Paul Tetlock, Pietro Veronesi, Marius Zoican, and seminar participants at Dauphine-Paris, Imperial College, London Conference on Activist Investors, and UC Irvine. We also thank T-C Lin for help with the IES options data. Jingyu Zhang provided excellent research assistance.

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

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

1 Introduction

Asymmetric information is ubiquitous in economics and finance. In a world with asymmetric information 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—illegal insider trading cases—in which we can 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 two types of information signals: (i) those based on aggregate trading volume, and (ii) those based on asset 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 two main messages: (1) options market reveals more information about informed trading than does equity market; (2) informed trading is more likely detected in volume than in prices.

One way to evaluate the quality of any information measure has been to test whether such

¹Theories 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 \(2009\)](#).

²Moreover, 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](#)).

measure predicts stock returns. We implement this test using a sample of individual daily stock returns of U.S. companies for the period 1995-2012, that is, one corresponding to our insider trading data. To account for both good and bad news coming to markets we focus on the predictability of absolute stock returns. We consider most commonly used information measures and group them into two categories: those based on prices and those based on trading volume. Our price-based measures include quoted and effective spread, price impact, and volatility; our volume-based measure is absolute order imbalance; while the mixture of the two signals is embedded in Kyle's lambda and the illiquidity measure. In our analysis, we assess the predictive power of our information measures for next-day and next-month returns. Our regression results show that almost all the measures correlate strongly with future returns. Using this evidence one could conclude that the measures are informative about the extent of private information revealed in financial markets. This interpretation, however, is not unique because the measures could be correlated with returns for reasons other than information. This is a spirit with which we believe our empirical context of insider trading is a superior way to evaluate the informational content of the signals.

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 spouse 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. The trades span a long period of 1995-2012 and represent the vast majority of industry sectors.

Our empirical tests utilize a standard event-study setting, 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 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 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. 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. We hypothesize that the coefficient of *Trade* should be statistically significant if a particular measure reveals private information. Our results indicate that stock-based measures generally do not reveal private information to markets. Of the nine measures we consider, only two—daily illiquidity and Kyle’s lambda—are statistically significant. Both of them combine information coming from prices and trading volume. Moreover, the significance of lambda disappears when we additionally include firm and time-fixed effects. Finally, the results remain similar when we benchmark the affected companies against a portfolio of firms in the same 2-digit SIC industry with a similar market capitalization. Overall, these results cast significant doubt on the interpretation of return-based predictability results as indicative of informed trading.

Next, we entertain similar tests for measures derived in options market. We again consider price-based and volume-based signals. The former group includes quoted spread, implied volatility, implied volatility spread, and skewness. The latter group includes levered option volume and ratios of option and underlying stock volume for call and put contracts. We find that, on average, option-based measures are more likely to reveal private information to markets. Of the nine measures we consider, six are statistically significant in the most comprehensive specification that considers fixed effects and the control group. 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. In addition, the levered option volume, based on out-of-the-money options, performs equally well. Finally, the coefficients for quoted option spread and implied volatility are also statistically significant. These results suggest that option-based measures might be better suited to detect private information in markets. This result is particularly interesting because prior research has mostly focused on stock-based measures.

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

³An 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. \(2015\)](#)).

⁴In 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 nonstrategically. 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 suggest that the patterns we document are unlikely a result of strategic motives for trading.

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. One 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 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.⁶ [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

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

⁶[Bhattacharya \(2014\)](#) provides an excellent review of the literature on both legal and illegal insider trading.

on price discovery.⁷

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.⁸ 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 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

⁷From a different perspective, [Ahern \(2015\)](#) provides a description of insider trading networks.

⁸A 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.

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 define our information measures. The results from returns regressions are discussed in Section 3. 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 Information Measures

In this section, we summarize various measures that we use as candidates to identify private information. Our choice of the measures is dictated by related theoretical models as well as their popularity in empirical studies. For clarity of exposition, we group measures according to whether they are based on equity or options data (in Sections 2.1 and 2.2) and, within each asset class, we further organize measures according to whether they are based on prices or trading volume.⁹ In each case, we briefly outline the motivating theoretical underpinning and then discuss the empirical implementation. Further details on the construction of the data are discussed in Section 2.3.

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.

⁹For exposition ease, we (arbitrarily) group measures that combine both prices and volume as ‘volume-based’. Of course, this is equivalent to classifying candidates as “price-only” and “other” measures. These grouping criteria reflect the fact that price-based measures were adopted earlier in and can thus be seen as the ‘standard’ approach (e.g., Glosten and Harris (1988)) to identify adverse selection.

Price-based Measures

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 security is given by

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

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.

Effective Spread (ES). The effective spread is given by the difference between the natural logarithm of the actual transaction price and the natural logarithm of the midpoint prevailing at the time of the trade. Formally,

$$ES_t = \sum_{k=1:K} 2\omega_k |\ln(p_k) - \ln(m_k)|,$$

where p_k is the price of the k -th trade, m_k is the mid-BBO quote at the moment the order was received, and ω_k represents a dollar weight for the k -th trade. The effective spread can be interpreted as a measure of the cost of executing a trade from the point of view of a trader submitting a marketable order.

Realized Spread (RS). The realized spread is given by

$$RS_t = \sum_{k=1:K} 2\omega_k d_k [\ln(p_k) - \ln(m_{k+5})],$$

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. The measure can be seen as the temporary component of the effective spread: It captures the revenue to liquidity providers assuming that the liquidity provider is able to close her position at the midpoint prevailing five minutes after the trade.

Price Impact (PI). Finally, the five-minute price impact is given by

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

where 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.

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

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

where $a_{\max,t}$ and $b_{\min,t}$ 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 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 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.

[Easley and O’Hara \(1992\)](#) pioneered the role of volume as a measure of adverse selection. In contrast to [Kyle \(1985\)](#) and [Glosten and Milgrom \(1985\)](#), liquidity providers in this model need not only learn both about the sign of private information, but about the occurrence of private information in the first place. Given that liquidity (noise) traders have perfectly inelastic demands, volume in this model is higher when there is an information event. Based on this notion, Easley et al. ([1996b](#); [1996a](#)) develop the probability of informed trading (PIN) empirical framework, which aims at measuring the adverse selection risk faced by uninformed traders.¹⁰ We follow [Easley et al. \(2008\)](#) and use the absolute order imbalance an alternative measure of the PIN, which has two

¹⁰Interestingly, [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.

distinct advantages. First, it can be computed over shorter periods. 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.

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

$$Lambda \text{ (slope): } r_n = \lambda \times \left(\sum_k d_k \sqrt{|vol_k|} \right)_n + error_n$$

where, for the n -th time interval period on date t , r_n is the stock return, vol_k is transaction k -th's dollar volume, and the bracketed term represents the signed volume over interval n . Intuitively, the slope of the regression measures the cost of demanding a certain amount of liquidity over a given time period. We report results based on 30-minute intervals.¹¹

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

$$DI_t = \frac{|r_t|}{vol_t}. \quad (1)$$

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.

Absolute order imbalance (AOI). The AOI on dat t is defined as

$$AOI_t = \left| \frac{Buys_t - Sells_t}{Buys_t + Sells_t} \right|,$$

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

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

2.2 Private Information in Option Markets

It is rather intuitive that privately informed agents trade options. [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 this Section are also useful in the analysis of derivatives, 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 Measures

[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 two additional measures of implied volatility. The first is 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. The second

is the implied volatility skewness, which measures the difference between the implied volatilities of out-of-the-money puts (OTMP) and at-the-money calls (ATMC). [Xing et al. \(2010\)](#) argue that the ability of this 'smirk' measure to predict earnings is consistent with, say, informed traders with negative news preferring to trade OTM put options (and thus these contracts become expensive relative to ATM calls).

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

Option Quoted Spread (QSO). Let t and i index trading dates and underlying stocks. Let $j = 1, \dots, J$ denote a strike-maturity combination. For any given underlying stock, the daily option bid-ask spread is defined as

$$QSO_t = \frac{1}{J} \sum_{j=1:J} \left(\frac{a_{jt} - b_{jt}}{m_{jt}} \right).$$

Implied Volatility (IV). The daily implied volatility is computed as an average of Option-Metrics' implied volatilities (*OMIV*)

$$IV_t = \frac{1}{J} \sum_{j=1:J} OMIV_j.$$

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

$$IVS_t = \sum_{j=1:J} \omega_j (OMIV_j^{CALL} - OMIV_j^{PUT}),$$

where ω_j denotes the open-interest weight that is computed using the average open interest in both call and put options. Only pairs with implied volatility and open interest records are included in the calculation.

Implied Volatility Skewness (IVSK). Following [Xing et al. \(2010\)](#), we compute

$$IVSK_t = OMIV_t^{OTMP} - OMIV_t^{ATMC}.$$

Following [Bakshi et al. \(1997\)](#), ATM status is given to cases where the underlying price is between $\pm 3\%$ of the strike. The terms $OMIV_t^{OTMP}$ and $OMIV_t^{ATMC}$ are computed as weighted averages,

as in the volatility spread calculation.

Volume-based Measures

[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.

Motivated by these theoretical literature, [Roll et al. \(2010\)](#) 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 (OS) measure. [Johnson and So \(2012\)](#) develop a model with short selling constraints and argue that, due to these constraints, high values of OS negatively predict future returns. This is because informed traders use options more when negative news arrive.¹² [Augustin et al. \(2015\)](#) conjecture that asymmetric information may increase the relative trade volume in OTM options. We thus consider a number of measures that relate option and stock volume as well as option volume across moneyness.¹³

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

¹²One 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.

¹³We 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.

Levered Option Volume (LOV). For call options on a given underlying stock, we define the levered option volume as

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

for all options on the same underlying stock. The intuition of this measure is simple: Informed traders value leverage and, therefore, a high LOV value may signal informed trading. In cases in which the denominator (but not the numerator) is equal to zero, we set the value of LOV to 100 (the 99% percentile of the empirical distribution).

Option/Stock (OS), Call/Stock (CS), and Put/Stock (PS) Volume Ratios. The OS ratio is given by

$$OS_t = \frac{\text{Option Volume}_t}{\text{Underlying Stock Volume}_t}.$$

Option volume includes the total volume in call and put options of all strikes and all maturities from OptionMetrics. We also consider CS and PS which are computed using call and put options volume in the numerator, respectively. Of course, $CS + PS = OS$.

Levered Option/Stock Volume (LOS). We consider a variation of the OS measure that is based on levered option volume, that we denote as LOS

$$LOS_t = \frac{\text{OTM Option Volume}_t}{\text{Underlying Stock Volume}_t}.$$

Signed OS Measures We follow [Ge et al. \(2015\)](#) and consider separate OS measures based on trade characteristics that can be identified using International Securities Exchange (ISE) data: buy/sell, call/put, and open/close. Therefore, we addition eight measures of option volume that are further scaled by stock volume: open buy call (OBC), open sell call (OSC), close buy call (CBC), close sell call (CSC), open buy put (OBP), open sell put (OSP), close buy put (CBP), and close sell put (CSP).

2.3 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 two sources. First, we use 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. Second, we use data from the International Securities Exchange (ISE) Open/Close Trade Profile, which also provides daily volume figures, but disaggregating records by whether the trades open new or close existing positions. 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.

Intraday Averages. In addition to dollar weighted averages, we also computed ES, RS, and PI using the number of shares as weights, obtaining similar results.

Trade Direction. We consider three trade-typing conventions to determine whether 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 Evidence from Returns Regressions

A traditional approach to evaluate the quality of information measures would be to see whether they can predict future rates of returns. Under the assumption that information that is traded on by informed investors is private, one would expect the market converge to the truth some time in the future and thus the return should be explained by the initial informed trade. If the informed trade is captured by the information measure then this would lead to a significant relationship between such measure and future returns.

We examine the predictability in stock returns by looking at two different return horizons:

a one-day and a one-month horizon. Since the information in the market might lead to either positive or negative return, we account for the two possibilities by taking an absolute value of return. Following the literature on short-horizon return predictability (e.g., [Tetlock et al., 2008](#)) we estimate the following linear regression model for the period 1995-2012:

$$ARET_{i,t+k} = a + b \times IM_{i,t} + c \times Controls_{i,t} + error_{i,t},$$

where $ARET_{i,t+k}$ is the absolute value of return on stock i at k -day horizon, $IM_{i,t}$ is the information measure for company i measured at time t , and $Controls$ is a vector of control variables. We additionally include 2-digit SIC industry fixed effects. To account for potential cross-correlation in residuals we cluster standard errors at the year-month dimension. Classical approaches to information measurement focus largely on stock-based measures of information. Hence, in our tests we only consider stock-based information measures, defined in [Section 2](#).

The control variables include the natural logarithm of market equity ($LNSIZE$), where market equity is calculated as the price per share times the number of shares outstanding; the natural logarithm of stock turnover ($LNTURNOVER$), where turnover is defined as trading volume divided by the number of shares outstanding; the daily stock return: contemporaneous, lagged one day, two days, and one month (RET); volatility of daily returns calculated over the past one month period ($VOLAT$); standardized earnings surprises (SUE), where SUE is defined as the difference between unexpected and expected earnings divided by the standard deviation of unexpected earnings calculated over the previous 20 quarters, unexpected earnings is the annual change in quarterly earnings, and expected earnings is the average of such changes measured over the 20 quarter period; the indicator variable equal one for the earnings announcement day ($EARNREP$); and the book to market equity ratio (B/M) defined as the ratio of book value of equity and market value of equity. Both SUE and B/M are winsorized at the 5% level. All control variables are obtained from CRSP and Compustat. In [Table 1](#), we present the summary statistics—mean, median, and standard deviation—for our information measures (Panels A and B) and all control variables (Panel C).

We report the results from the estimation for one-day returns in [Table 2](#). The results indicate a statistically significant predictability in one-day returns for eight out of nine information measures. The only insignificant coefficient is that of DI . The coefficients of the control variables are consistent

with prior findings. Size, and one-day lagged returns are negative and significant, whereas the coefficients of turnover, SUE , and B/M are all positive and significant. The remaining coefficients are insignificant.

Similarly, in Table A1 of the Online Appendix we report the results for stock returns one month ahead. All coefficients are statistically significant this time. Based on the above evidence academics often conclude that the commonly used measures are informative about the extent of private information revealed in financial markets. This interpretation, however, is only one among many others since the information measures could be correlated with returns for reasons other than information. Therefore, we now turn into a sharper empirical design, that of illegal insider trading, in which we can actually observe instances in which private information is used in financial markets.

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.¹⁴ 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 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,

¹⁴We collected online all the files in 2013. At the time of collection, the oldest available complaint file was for the year 2001.

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 3 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 4, 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 cyclicity 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.

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.¹⁵ 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:

$$IM_{it} = a + b \times TRADE_i + c \times Controls_{it} + d_i + e_t + error_{it}. \quad (2)$$

where $IM_{i,t}$ is the information measure for company i measured at time t . Throughout all

¹⁵In 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.

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

The identifying assumption of the above model is that any time-series variation in information measure around insider trading days is unlikely to be correlated with any other observable than the trading itself. However, this assumption generally need not be true, in which case our results could be subject to omitted variable bias.¹⁶ 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 4 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.

¹⁶In 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.

Our control portfolio is composed of firms that belong to the same 2-digit SIC industry and the same market capitalization quintile. Subsequently, we calculate the arithmetic average of a given information measure in the portfolio and subtract this average from the information measure, which results in a controls-adjusted information measure ($CAIM$). The construction of our estimation window follows the same principles as before, and the difference-in-differences estimation is equivalent to estimating a regression model in (2) except that we replace IM with $CAIM$.

$$CAIM_{it} = a + b \times TRADE_{it,t-k} + c \times Controls_{it} + d_i + e_t + error_{it}. \quad (3)$$

5.2 Baseline Results

In Table 5, 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 nine 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 6 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: *OS*, *CS*, *PS*, and *LOS*. The pure volume based measure *LOV* does not correlate strongly with *TRADE*. Of the measures based on option prices *QSO* and *IV* show the most robust behavior and *IVSK* is significant only in the specification without fixed effects.

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 10.

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 activi-

ties 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 7.

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 QSO 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 8. In all panels, we report the results that mimic the design of Panels B and D in Table 5 (with *CAIM* as the dependent variable). Compared to the results in Panel B of Table 5, 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 B4 with those in Panel D of Table 5. Our main finding is that all the previously significant coefficients for price-based measures (*QSO* 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 *OS* 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 9. The results for stocks-only trades in Panels A and B indicate patterns that closely mimic those in Table 5. 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 10 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 *IVSK* and *LOV*. 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 *LOV*. 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 11. 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 (*QSO* and *IV*) and volume-based measures (*OS*, *CS*, *PS*, and *LOS*). 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 *LOS* 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 12 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 (*OS* and *CS*) and statistically significant at the 5% level for *LOV*. 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 B5 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 , OS , CS , and 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. This distinction makes sense from the perspective of the insider trading which by design is one sided.

In this section, we use the measures with signed option volume to provide further insights on the importance of trade origination. We distinguish between trades that originate in the buy and sell side. In addition, we compare trades that happen at the open and at the close of the trade. The benefit of using signed volume measures is compromised by the fact that our data are smaller because the data provider (ISE) only captures about one third of the Option Metrics volume. Specifically, we estimate regression models for controls-adjusted measures and report the results in Table 13.

The results 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 is measured at the open. This might suggest that insider trades are usually executed at the open of the market. Also, this result corroborates the evidence in [Johnson and So \(2012\)](#) and [Ge et al. \(2015\)](#).

6 Concluding Remarks

Information is a cornerstone of financial decision making but also one that is difficult to observe. Academic research to date has taken several attempts to identify informed trading but much of the effort to design measures of information is empirically challenged by dealing with confounding effects and inherent measurement noise. In an ideal experiment, one would like to know when private information is used and how it is reflected in market observables, such as volume and prices. Our goal is to design an experiment which is close to satisfying such a requirement. Insider trading is based on non-public and material information and detailed information about the characteristics of the trades makes it possible to evaluate the performance of various candidates for good information measures.

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. A similar result holds for measures that mix information from both markets. Second, we show that information contained in trade volume is generally more useful to predict informed trading than is information contained in prices. Given that much of the theoretical research to date has largely looked into prices as signals of information this result might call for more effort to include volume in studies of trade.

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 associated with strategic incentives to reduce illiquidity costs, which suggests that illiquidity costs might be smaller compared to the benefits of using information in a fast manner. 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 \(2014\)](#).

We believe our framework is a promising direction to validate several of the theoretical and empirical discoveries in information economics. It is also a great platform for evaluating new studies

that would examine informational properties of financial markets. We leave these exciting endeavors for future research.

References

- ADMATI, A. R. (1985): “A Noisy Rational Expectations Equilibrium for Multi-Asset Securities Markets,” *Econometrica*, 53, 629–658.
- AHERN, K. R. (2015): “Information networks: evidence from illegal insider trading tips,” *USC Working paper*, 1–86.
- ALI, U. AND D. HIRSHLEIFER (2015): “Opportunism as a Firm and Managerial Trait : Predicting Insider Trading Profits and Misconduct,” *Working Paper*.
- AMIHUD, Y. (2002): “Illiquidity and stock returns: cross-section and time-series effects,” *Journal of Financial Markets*, 5, 31–56.
- AUGUSTIN, P., M. BRENNER, AND M. SUBRAHMANYAM (2015): “Informed Options Trading prior to M&A Announcements: Insider Trading?” .
- BACK, K. (1993): “Asymmetric information and options,” *Review of Financial Studies*, 44, 421–428.
- BACK, K., C. CAO, AND G. A. WILLARD (2000): “Imperfect Competition among Informed Traders,” *Journal of Finance*, 55, 2117–2155.
- BAKSHI, G. S., C. CAO, AND Z. CHEN (1997): “Empirical Performance of Alternative Option Pricing Models,” *The Journal of Finance*, 52, 2003–2049.
- BANERJEE, S. AND B. GREEN (2015): “Signal or noise? Uncertainty and learning about whether other traders are informed,” *Journal of Financial Economics*, 117, 398–423.
- BARNDORFF-NIELSEN, O. E. AND N. SHEPHARD (2002): “Econometric analysis of realized volatility and its use in estimating stochastic volatility models,” *Journal of the Royal Statistical Society. Series B: Statistical Methodology*, 64, 253–280.
- BHATTACHARYA, U. (2014): “Insider Trading Controversies: A Literature Review,” *Annual Review of Financial Economics*, 6, 385–403.
- BIAIS, B., L. R. GLOSTEN, AND C. S. SPATT (2005): “Market microstructure: A survey of microfoundations, empirical results, and policy implications,” *Journal of Financial Markets*, 8, 217–264.
- BIAIS, B. AND P. HILLION (1994): “Insider and liquidity trading in stock and options markets,” *Review of Financial Studies*, 7, 743–780.
- BLACK, F. (1975): “Fact and Fantasy in the Use of Options,” *Financial Analysts Journal*, 31, 36–41.
- BLUME, L., D. EASLEY, AND M. O’HARA (1994): “Market Statistics and Technical Analysis : The Role of Volume,” *The Journal of Finance*, 49, 153–181.
- BOULATOV, A., T. HENDERSHOTT, AND D. LIVDAN (2013): “Informed Trading and Portfolio Returns,” *Review of Economic Studies*, 80, 35–72.
- BRENNAN, M. J. AND H. H. CAO (1996): “Information, Trade, and Derivative Securities,” *Review of Financial Studies*, 9, 163–208.
- CAMPBELL, J. Y., S. J. GROSSMAN, AND J. WANG (1993): “Trading volume and serial correlation in stock returns,” *The Quarterly Journal of . . .*, 905 –.

- CAMPBELL, J. Y. AND A. S. KYLE (1993): “Smart Money, Noise Trading and Stock Price Behaviour,” *Review of Economic Studies*, 60, 1–34.
- CESPA, G. AND T. FOUCAULT (2014): “Illiquidity Contagion and Liquidity Crashes,” *Review of Financial Studies*, 27, 1615–1660.
- CHAE, J. (2005): “Trading Volume, Information Asymmetry, and Timing Information,” *Journal of Finance*, 60, 413–442.
- CHAKRABARTY, B., B. LI, V. NGUYEN, AND R. A. VAN NESS (2007): “Trade classification algorithms for electronic communications network trades,” *Journal of Banking & Finance*, 31, 3806–3821.
- COHEN, L., A. FRAZZINI, AND C. MALLOY (2008): “The Small World of Investing: Board Connections and Mutual Fund Returns Andrea Frazzini,” *Journal of Political Economy*, 116.
- COHEN, L., C. MALLOY, AND L. POMORSKI (2012): “Decoding Inside Information,” *The Journal of Finance*, 67, 1009–1043.
- COLLIN-DUFRESNE, P. AND V. FOS (2015): “Do Prices Reveal the Presence of Informed Trading?” *The Journal of Finance*, 70, 1555–1582.
- COLLIN-DUFRESNE, P., V. FOS, AND D. MURAVYEV (2015): “Informed Trading and Option Prices: Evidence from Activist Trading,” *Working Paper, Boston College*.
- CORNELL, B. AND E. R. SIRRI (1992): “The Reaction of Investors and Stock Prices to Insider Trading,” *Journal of Finance*, 47, 1031–1059.
- CORWIN, S. A. AND P. SCHULTZ (2012): “A Simple Way to Estimate Bid-Ask Spreads from Daily High and Low Prices,” *The Journal of Finance*, 67, 719–760.
- CREMERS, M. AND D. WEINBAUM (2010): “Deviations from Put-Call Parity and Stock Return Predictability,” *Journal of Financial and Quantitative Analysis*, 45, 335–367.
- DE LONG, B., A. SHLEIFER, L. SUMMERS, AND R. WALDMANN (1990): “Noise Trader Risk in Financial Markets,” *Journal of Political Economy*, 98, 703–738.
- DE LONG, J. B., A. SHLEIFER, L. H. SUMMERS, AND R. J. WALDMANN (1990): “Positive Feedback Investment Strategies and Destabilizing Rational Speculation,” *Journal of Finance*, 45, 379–395.
- DEL GUERCIO, D., E. R. ODDERS-WHITE, AND M. J. READY (2013): “The Deterrence Effect of SEC Enforcement Intensity on Illegal Insider Trading,” *Working Paper, University of Wisconsin*.
- EASLEY, D., R. F. ENGLE, M. O’HARA, AND L. WU (2008): “Time-varying arrival rates of informed and uninformed trades,” *Journal of Financial Econometrics*, 171–207.
- EASLEY, D., N. M. KIEFER, AND M. O’HARA (1996a): “Cream-skimming or profit-sharing? The curious role of purchased order flow,” *Journal of Finance*, 51, 811–833.
- EASLEY, D., N. M. KIEFER, M. O’HARA, AND J. B. PAPERMAN (1996b): “Liquidity, information, and infrequently traded stocks,” *Journal of Finance*, 51, 1405–1436.
- EASLEY, D. AND M. O’HARA (1987): “Price, trade size, and information in securities markets,” *Journal of Financial Economics*, 19, 69–90.
- (1992): “Time and the process of security price adjustment,” *Journal of Finance*, 47, 577–605.
- (2004): “Information and the Cost of Capital,” *The Journal of Finance*, 59, 1553–1583.
- EASLEY, D., M. O’HARA, AND P. S. SRINIVAS (1998): “Option volume and stock prices: Evidence on where informed traders trade,” *Journal of Finance*, 53, 431–465.

- ELLIS, K., R. MICHAELY, AND M. O'HARA (2000): "The Accuracy of Trade Classification Rules: Evidence from Nasdaq," *Journal of Financial and Quantitative Analysis*, 35, 529–551.
- FOSTER, D. F. AND S. VISWANATHAN (1996): "Strategic Trading When Agents Forecast the Forecasts of Others," *Journal of Finance*, 51, 1437–1478.
- FRIEDMAN, M. (1953): "The case for flexible exchange rates," in *Essays in Positive Economics*, Chicago, IL: University of Chicago Press.
- GE, L., T.-C. LIN, AND N. D. PEARSON (2015): "Why does the Option to Stock Volume Ratio Predict Stock Returns ?" *Journal of Financial Economics (Forthcoming)*.
- GLOSTEN, L. R. AND L. E. HARRIS (1988): "Estimating the components of the bid/ask spread," *Journal of Financial Economics*, 21, 123–142.
- GLOSTEN, L. R. AND P. R. MILGROM (1985): "Bid, ask and transaction prices in a specialist market with heterogeneously informed traders," *Journal of Financial Economics*, 14, 71–100.
- GOYENKO, R. Y., C. W. HOLDEN, AND C. A. TRZCINKA (2009): "Do liquidity measures measure liquidity?" *Journal of Financial Economics*, 92, 153–181.
- GROSSMAN, S. J. (1976): "On the efficiency of competitive stock markets where trades have diverse information," *Journal of Finance*, 31, 573–585.
- GROSSMAN, S. J. AND J. STIGLITZ (1980): "On the impossibility of informationally efficient markets," *The American Economic Review*, 70, 393–408.
- HARRIS, M. AND A. RAVIV (1993): "Differences of Opinion Make a Horse Race," *Review of Financial Studies*, 6, 473–506.
- HASBROUCK, J. (2009): "Trading Costs and Returns for U.S. Equities: Estimating Effective Costs from Daily Data," *Journal of Finance*, 64, 1445–1477.
- HE, H. AND J. WANG (1995): "Differential Informational and Dynamic Behavior of Stock Trading Volume," *Review of Financial Studies*, 8, 919–972.
- HELLWIG, M. F. (1980): "On aggregation of information in competitive markets," *Journal of Economic Theory*, 22, 477–498.
- HENDERSHOTT, T., D. LIVDAN, AND N. SCHÜRHOFF (2015): "Are institutions informed about news?" *Journal of Financial Economics*, 117, 249–287.
- HOLDEN, C. W., S. E. JACOBSEN, AND A. SUBRAHMANYAM (2014): "The Empirical Analysis of Liquidity," *Foundations and Trends in Finance*, 8, 263–365.
- HOLDEN, C. W. AND A. SUBRAHMANYAM (1992): "Long-lived private information and imperfect competition," *Journal of Finance*, 47, 481–487.
- HUANG, R. D. AND H. R. STOLL (1996): "Dealer versus auction markets: A paired comparison of Execution Costs on NASDAQ and NYSE," *Journal of Financial Economics*, 41, 313–357.
- JOHN, K. AND M. G. SUBRAHMANYAM (2003): "Margin Rules, InTrading in derivatives and Price Dynamic," *Working Paper, NYU Stern*.
- JOHNSON, T. L. AND E. C. SO (2012): "The option to stock volume ratio and future returns," *Journal of Financial Economics*, 106, 262–286.
- KACPERCZYK, M. AND A. SERU (2007): "Fund Manager Use of Public Information: New Evidence on Managerial Skills," *Journal of Finance*, LXII, 485–528.
- KACPERCZYK, M., S. VAN NIEUWERBURGH, AND L. VELDKAMP (2014): "Time-Varying Fund Manager Skill," *The Journal of Finance*, 69, 1455–1484.

- KIM, O. (1991): “Market reaction to anticipated announcements,” *Journal of Financial Economics*, 30, 273–309.
- KYLE, A. S. (1985): “Continuous Auctions and Insider Trading,” *Econometrica*, 53, 1315–1335.
- LEE, C. M. C. AND M. J. READY (1991): “Inferring Trade Direction from Intraday Data,” *Journal of Finance*, 46, 733.
- MEULBROEK, L. K. (1992): “An Empirical Analysis of Illegal Insider Trading,” *Journal of Finance*, 47, 1661–1699.
- ROLL, R., E. SCHWARTZ, AND A. SUBRAHMANYAM (2010): “O/S: The relative trading activity in options and stock,” *Journal of Financial Economics*, 96, 1–17.
- SCHNEIDER, J. (2009): “A Rational Expectations Equilibrium with Informative Trading Volume,” *The Journal of Finance*, 64, 2783–2805.
- TETLOCK, P. C., M. SAAR-TSECHANSKY, AND S. MACSKASSY (2008): “More than words: Quantifying language to measure firms fundamentals,” *Journal of Finance*, 63, 1437–1467.
- VANDEN, J. M. (2008): “Information quality and options,” *Review of Financial Studies*, 21, 2635–2676.
- VAYANOS, D. AND J. WANG (2013): “Market Liquidity: Theory and Empirical Evidence,” in *Handbook of the Economics of Finance*, Elsevier B.V., vol. 2, 1289–1361.
- WANG, J. (1993): “A Model of Intertemporal Asset Prices Under Asymmetric Information,” *The Review of Economic Studies*, 60, 249.
- (1994): “A Model of Competitive Stock Trading Volume,” *Journal of Political Economy*, 102, 127–168.
- XING, Y., X. ZHANG, AND R. ZHAO (2010): “What Does the Individual Option Volatility Smirk Tell Us about Future Equity Returns?” *Journal of Financial and Quantitative Analysis*, 45, 641–662.

Appendix: List of Information Measures

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

Stock-based Measures

- QS: Quoted bid–ask spread for stocks (TAQ NBBO) as a percent of the midquote. Time weighted daily average.
- ES: Effective spread for stocks (NBBO). Dollar-weighted daily average.
- RS: Realized spread for stocks (NBBO). Five-minutes midquote change. Dollar-weighted daily average. Lee-Ready trade sign classification.
- 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 (from OptionMetrics) The following are the baseline option-based measures from OptionMetrics data. OMIV denotes OptionMetrics' reported implied volatility.

- QSO: Daily arithmetic average of quoted bid–ask spread for all traded options on the same underlying.
- IV: 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.
- IVSK: Implied volatility skewness, given by the average difference between the OMIV of out-of-the-money puts and at-the-money calls. Open–interest-weighted average.
- LOV: Levered option volume, given by the ratio $OTM/(ATM+ITM)$ option volume for all traded options on the same underlying
- OS: Total option volume/Stock volume.
- OC: Total call volume/Stock volume.
- OP: Total put volume/Stock volume.
- LOS: Total OTM option volume/Stock volume.

Option-based Measures (ISE Open/Close data) The following are the signed option-based measures the International Securities Exchange Open/Close data.

- OBC: Open buy call/ Stock volume
- OSC: Open sell call/ Stock volume
- CBC: Close buy call/ Stock volume
- CSC: Close sell call/ Stock volume
- OBP: Open buy put/ Stock volume
- OSP: Open sell put/ Stock volume
- CBP: Close buy put/ Stock volume
- CSP: Close sell put/ Stock volume

Figure 2. Information Measures in the 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 1
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** shows summary statistics for the control variables in Tables 2 and A1. *RET* is the daily stock return, *RET_M* is the monthly stock return, *VOL_M* is the volatility of daily stock returns calculated within a month, *SUE* is the standardized unexpected earnings, and *B/M* is the ratio of book value of equity and market value of equity. All measures have been winsorized at the 1% level. Information measures in Panels A and B are defined in Section 2.

Variable	mean	median	st.dev.
Panel A: Stock-based measures			
QS	0.5670	0.2096	0.8918
ES	0.5729	0.2364	0.8448
RS	0.4512	0.1563	0.7333
PI	0.1061	0.0458	0.1794
RV	0.0855	0.0345	0.1333
PR	0.0459	0.0345	0.0395
Lambda	0.0225	0.0013	0.0617
DI	0.9913	0.0444	3.9680
AOI	0.1546	0.1111	0.1490
Panel B: Option-based measures			
QSO	0.5109	0.4691	0.2393
IV	0.5314	0.4881	0.2250
IVS	-0.0121	-0.0074	0.0530
IVSK	0.0991	0.0863	0.0752
LOV	29.19	1.87	43.54
OS	0.0011	0.0004	0.0020
CS	0.0007	0.0002	0.0012
PS	0.0004	0.0001	0.0009
LOS	0.0006	0.0002	0.0011
Panel C: Return regression variables			
RET	0.0011	0.0000	0.0521
RET_M	0.0244	0.0064	0.2547
VOL_M	0.0367	0.0295	0.0269
SUE	-0.1076	0.0000	1.6463
B/M	0.4159	0.3313	0.4711

TABLE 2
Daily Returns and Stock-based Information Measures

The dependent variable is daily absolute stock return, $ARET$, measured at the company level at time $t+1$ over the period 1995-2012. The independent variables, measured at the daily frequency, include information measures (defined in Section 2). $LNSIZE$ is the natural logairthm of the market value of equity. $LNTURN$ is the natural logarithm of the stock turnover defined as the ratio of dfaily volume and number of shares outstanding. RET_1 and RET_2 are the daily stock returns measured at times $t-1$ and $t-2$, respectively. RET_M is the monthly stock return. $EARNREP$ is an indicator variable equal to one for days when earnings are reported. VOL_M is the volatility of daily stock returns calculated within a month, SUE is the standardized unexpected earnings, and B/M is the ratio of book value of equity and market value of equity. All regressions include 2-digit SIC industry fixed effects. All information measures, SUE , and B/M have been winsorized at the 1% level. All information measures, measured as of time t , are winsorized at the 1% level. Standard errors (in parentheses) are clustered at the time dimension. ***, **, * denote 1%, 5%, and 10% level of statistical significance, respectively.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
QS	0.003*** (0.000)								
ES		0.005*** (0.000)							
RS			0.005*** (0.000)						
PI				0.011*** (0.002)					
RV					0.073*** (0.003)				
PR						0.228*** (0.010)			
Lambda							0.043*** (0.010)		
DI								0.015 (0.014)	
AOI									-0.003*** (0.001)
LNSIZE	-0.001*** (0.000)	-0.000*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)
LNTURN	0.114*** (0.016)	0.117*** (0.016)	0.111*** (0.016)	0.105*** (0.015)	0.054** (0.023)	0.020 (0.013)	0.112*** (0.023)	0.099*** (0.015)	0.097*** (0.015)
RET	-0.002 (0.010)	-0.001 (0.010)	-0.001 (0.010)	-0.002 (0.010)	-0.007 (0.008)	-0.005 (0.009)	-0.003 (0.008)	-0.001 (0.010)	-0.001 (0.010)
RET_1	0.001 (0.005)	0.001 (0.005)	0.001 (0.005)	0.001 (0.005)	-0.002 (0.006)	0.001 (0.004)	-0.004 (0.007)	0.001 (0.005)	0.001 (0.005)
RET_2	-0.000 (0.006)	-0.000 (0.006)	0.000 (0.006)	-0.000 (0.006)	0.014 (0.011)	-0.000 (0.004)	0.013 (0.012)	-0.001 (0.006)	-0.000 (0.006)
RET_M	-0.012*** (0.002)	-0.011*** (0.002)	-0.012*** (0.002)	-0.012*** (0.002)	-0.008*** (0.002)	-0.008*** (0.001)	-0.011*** (0.003)	-0.012*** (0.002)	-0.012*** (0.002)

TABLE 2
Daily Returns and Stock-based Information Measures (continued)

VOL_M	0.384*** (0.023)	0.372*** (0.023)	0.376*** (0.024)	0.397*** (0.023)	0.178*** (0.018)	0.241*** (0.013)	0.290*** (0.025)	0.405*** (0.025)	0.406*** (0.025)
SUE	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
EARNREP	0.026*** (0.001)	0.026*** (0.001)	0.026*** (0.001)	0.026*** (0.001)	0.026*** (0.002)	0.023*** (0.001)	0.029*** (0.003)	0.027*** (0.001)	0.026*** (0.001)
B/M	-0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)	0.001 (0.002)	0.000 (0.001)	0.000 (0.002)	0.000 (0.001)	0.000 (0.001)
Constant	0.020*** (0.002)	0.015*** (0.002)	0.018*** (0.002)	0.025*** (0.002)	0.028*** (0.003)	0.016*** (0.001)	0.032*** (0.003)	0.031*** (0.002)	0.032*** (0.002)
Observations	228,501	228,501	228,428	228,426	57,728	228,501	57,728	228,185	228,428

TABLE 3
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 4
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 4
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
Depository 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 5
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 2. **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.

	QS	ES	RS	PI	RV	PR	Lambda	DI	AOI
Panel A: Baseline estimates									
TRADE	-0.014 (0.039)	-0.011 (0.033)	-0.015 (0.029)	0.003 (0.006)	0.010 (0.007)	0.003 (0.002)	-0.007** (0.003)	-0.184* (0.097)	0.001 (0.005)
LNSIZE	-0.196*** (0.054)	-0.251*** (0.057)	-0.198*** (0.050)	-0.048*** (0.009)	-0.053*** (0.007)	-0.011*** (0.002)	-0.021*** (0.003)	-0.029 (0.142)	0.001 (0.005)
LNVOL	-0.081* (0.041)	-0.031 (0.043)	-0.037 (0.039)	0.010 (0.006)	0.032*** (0.005)	0.005*** (0.001)	0.010*** (0.003)	-0.519*** (0.158)	-0.035*** (0.005)
TURNOVER	-2.842 (2.631)	-3.972 (2.516)	-1.935 (2.277)	-1.657*** (0.396)	0.790** (0.377)	1.027*** (0.108)	-0.834*** (0.157)	-6.103 (6.924)	0.727** (0.297)
PRC	0.000 (0.002)	0.001 (0.003)	0.001 (0.002)	0.000 (0.000)	0.001*** (0.000)	-0.000 (0.000)	0.000** (0.000)	-0.001 (0.007)	-0.001* (0.000)
Constant	4.243*** (0.463)	4.349*** (0.439)	3.559*** (0.377)	0.648*** (0.062)	0.350*** (0.038)	0.116*** (0.012)	0.193*** (0.021)	7.811*** (1.305)	0.596*** (0.039)
#Obs	6,860	6,860	6,856	6,856	6,595	7,041	6,860	6,991	6,856
Panel B: With firm fixed effects									
TRADE	-0.039 (0.024)	-0.020 (0.019)	-0.021 (0.017)	0.001 (0.005)	0.007 (0.005)	0.002* (0.001)	-0.003 (0.002)	-0.410*** (0.141)	0.000 (0.005)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	6,860	6,860	6,856	6,856	6,595	7,041	6,860	6,991	6,856
Panel C: With time and firm fixed effects									
TRADE	-0.042* (0.022)	-0.016 (0.018)	-0.018 (0.017)	0.000 (0.005)	0.007 (0.004)	0.003*** (0.001)	-0.003 (0.002)	-0.416*** (0.142)	-0.001 (0.004)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	6,874	6,874	6,870	6,870	6,609	7,055	6,874	7,005	6,870
Panel D: With time and firm fixed effects (control group adjusted)									
TRADE	-0.059 (0.094)	0.001 (0.008)	-0.007 (0.012)	0.001 (0.003)	-0.002 (0.002)	0.003*** (0.001)	-0.002 (0.001)	-0.392*** (0.137)	0.002 (0.002)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	6,874	6,874	6,874	6,870	6,609	7,055	6,874	7,005	6,870

TABLE 6
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 2. **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.

	QSO	IV	IVS	IVSK	LOV	OS	CS	PS	LOS
Panel A: Baseline estimates									
TRADE	-0.023* (0.012)	0.013 (0.013)	0.002 (0.003)	-0.011* (0.006)	-0.803 (2.267)	0.001*** (0.000)	0.001*** (0.000)	0.000** (0.000)	0.001*** (0.000)
LNSIZE	-0.055*** (0.015)	-0.109*** (0.016)	0.000 (0.002)	-0.015** (0.006)	-6.911*** (1.831)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
LNVOL	0.015 (0.015)	0.062*** (0.013)	-0.001 (0.002)	0.010** (0.005)	-2.800* (1.622)	0.000*** (0.000)	0.000** (0.000)	0.000*** (0.000)	0.000** (0.000)
TURNOVER	-3.579*** (0.735)	1.403* (0.806)	-0.015 (0.139)	-0.809*** (0.301)	-824.559*** (97.011)	0.003 (0.007)	0.003 (0.004)	0.001 (0.003)	0.002 (0.004)
PRC	-0.004*** (0.001)	-0.000 (0.001)	-0.000 (0.000)	0.001** (0.000)	-0.178** (0.089)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Constant	1.251*** (0.116)	1.232*** (0.109)	0.010 (0.016)	0.150*** (0.036)	182.851*** (12.341)	-0.002** (0.001)	-0.001* (0.001)	-0.001*** (0.000)	-0.001** (0.000)
#Obs	4,932	4,850	4,932	2,135	4,932	4,932	4,931	4,932	4,932
Panel B: With firm fixed effects									
TRADE	-0.018* (0.010)	0.016** (0.007)	0.002 (0.003)	-0.003 (0.005)	-0.356 (2.298)	0.001*** (0.000)	0.001*** (0.000)	0.000*** (0.000)	0.001*** (0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	4,932	4,850	4,932	2,135	4,932	4,932	4,931	4,932	4,932
Panel C: With time and firm fixed effects									
TRADE	-0.025** (0.010)	0.015** (0.007)	0.002 (0.003)	-0.007 (0.005)	-0.956 (2.321)	0.001*** (0.000)	0.001*** (0.000)	0.000*** (0.000)	0.001*** (0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	4,932	4,850	4,932	2,135	4,932	4,932	4,931	4,932	4,932
Panel D: With time and firm fixed effects (control group adjusted)									
TRADE	-0.023** (0.009)	0.018** (0.007)	0.002 (0.003)	-0.001 (0.004)	-1.571 (2.234)	0.001*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	4,932	4,850	4,932	2,135	4,932	4,932	4,931	4,932	4,932

TABLE 7
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 2. 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	ES	RS	PI	RV	PR	Lambda	DI	AOI
Panel A: Stock-based measures: One firm									
TRADE	-0.077** (0.036)	-0.032 (0.029)	-0.034 (0.028)	0.003 (0.008)	0.008 (0.007)	0.001 (0.002)	-0.003 (0.003)	-0.521** (0.218)	-0.001 (0.007)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	3,511	3,511	3,507	3,507	3,395	3,654	3,395	3,616	3,507
Panel B: Stock-based measures: Two or more firms									
TRADE	-0.008 (0.029)	0.007 (0.022)	0.005 (0.020)	-0.002 (0.006)	0.004 (0.005)	0.005** (0.002)	-0.004 (0.003)	-0.237 (0.150)	-0.003 (0.005)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	3,334	3,334	3,334	3,334	3,200	3,387	3,334	3,375	3,334
	QSO	IV	IVS	IVSK	LOV	OS	CS	PS	0.343
Panel C: Option-based measures: Single firm									
TRADE	-0.005 (0.013)	0.013 (0.010)	0.001 (0.004)	-0.004 (0.004)	0.117 (2.818)	0.001*** (0.000)	0.000*** (0.000)	0.000 (0.000)	0.000*** (0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	2,458	2,443	2,458	1,167	2,458	2,458	2,458	2,458	2,458
Panel D: Option-based measures: Two or more firms									
TRADE	-0.039*** (0.013)	0.026** (0.011)	0.002 (0.004)	0.002 (0.007)	-3.516 (3.216)	0.001*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.001*** (0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	2,474	2,407	2,474	968	2,474	2,474	2,473	2,474	2,474

TABLE 8
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 2. **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). 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	ES	RS	PI	RV	PR	Lambda	DI	AOI
Panel A: Trade within two days of information acquisition									
TRADE	0.012 (0.025)	-0.003 (0.018)	-0.010 (0.015)	-0.003 (0.005)	-0.000 (0.003)	0.002 (0.002)	-0.006* (0.003)	-0.433** (0.212)	0.003 (0.006)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	2,068	2,068	2,065	2,065	1,978	2,106	2,068	2,095	2,065
Panel B: Number of same-trader trades less than or equal to 7									
TRADE	-0.002 (0.015)	-0.000 (0.012)	-0.009 (0.012)	0.003 (0.004)	-0.002 (0.002)	0.002 (0.002)	-0.002 (0.002)	-0.347* (0.180)	0.002 (0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	3,536	3,536	3,533	3,533	3,389	3,691	3,536	3,659	3,533
Panel C: Number of trades per company less than or equal to 5									
TRADE	-0.009 (0.021)	0.015 (0.012)	0.018 (0.014)	0.002 (0.006)	-0.002 (0.003)	0.001 (0.002)	-0.006** (0.003)	-0.279* (0.165)	0.001 (0.004)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	3,101	3,101	3,100	3,100	2,984	3,167	3,101	3,152	3,100
Panel D: Number of trades per legal case less than 15									
TRADE	-0.007 (0.016)	0.005 (0.011)	-0.005 (0.012)	0.007* (0.004)	-0.005** (0.002)	0.001 (0.002)	-0.003 (0.002)	-0.618* (0.259)	0.001 (0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	3,488	3,488	3,484	3,484	3,368	3,648	3,488	3,609	3,484
Panel E: Profits lower than \$100k									
TRADE	-0.054* (0.030)	-0.019 (0.023)	-0.023 (0.024)	0.002 (0.008)	0.010* (0.006)	0.003* (0.001)	-0.003 (0.002)	-0.493** (0.226)	0.003 (0.007)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	3,856	3,856	3,852	3,852	3,657	3,921	3,657	3,878	3,852

TABLE 9
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 2. **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	ES	RS	PI	RV	PR	Lambda	DI	AOI
Panel A: Stocks-only trades with time and firm fixed effects									
TRADE	-0.047*	-0.017	-0.018	-0.001	0.006	0.003**	-0.003	-0.458***	0.001
	(0.025)	(0.020)	(0.019)	(0.006)	(0.005)	(0.001)	(0.003)	(0.157)	(0.005)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	6,122	6,122	6,118	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	-0.002	0.001	-0.003	0.003**	-0.002	-0.433***	0.003
	(0.013)	(0.009)	(0.009)	(0.003)	(0.002)	(0.001)	(0.002)	(0.152)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	6,122	6,122	6,118	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	-0.001	-0.003	0.012**	0.004	0.001	-0.001	-0.027**	-0.003
	(0.009)	(0.008)	(0.007)	(0.005)	(0.003)	(0.001)	(0.001)	(0.013)	(0.005)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	2,434	2,434	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	-0.009	-0.011*	0.004	-0.001	0.001	-0.000	-0.015	0.002
	(0.008)	(0.007)	(0.006)	(0.004)	(0.002)	(0.001)	(0.001)	(0.012)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	2,434	2,434	2,434	2,434	2,386	2,451	2,434	2,451	2,434

TABLE 10
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 2. **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.

	QSO	IV	IVS	IVSK	LOV	OS	CS	PS	LOS
Panel A: Options-only trades with time and firm fixed effects									
TRADE	-0.040*** (0.013)	0.016*** (0.006)	0.005** (0.003)	0.001 (0.006)	0.805 (3.043)	0.001*** (0.000)	0.001*** (0.000)	0.000*** (0.000)	0.001*** (0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	2,344	2,344	2,344	1,216	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*** (0.013)	0.020*** (0.006)	0.007** (0.003)	0.004 (0.005)	-0.111 (2.952)	0.001*** (0.000)	0.001*** (0.000)	0.000*** (0.000)	0.001*** (0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	2,344	2,344	2,344	1,216	2,344	2,344	2,344	2,344	2,344
Panel C: Stocks-only trades with time and firm fixed effects									
TRADE	-0.025** (0.011)	0.016** (0.008)	0.001 (0.003)	-0.010*** (0.004)	-0.076 (2.441)	0.001*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	4,248	4,166	4,248	1,783	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** (0.010)	0.020** (0.008)	0.001 (0.003)	-0.004 (0.003)	-0.705 (2.327)	0.001*** (0.000)	0.000*** (0.000)	0.000** (0.000)	0.000*** (0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	4,248	4,166	4,248	1,783	4,248	4,248	4,247	4,248	4,248

TABLE 11
Conditioning on Event Type

The dependent variables are stock-based information measures (in **Panels A-C**) and option-based information measures (in **Panels D-F**), 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 2. In **Panels A and D**, we consider trades related to mergers and acquisitions; in **Panels B and E**, trades related to earnings announcements; in **Panels C and F**, trades related to all other events. 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	ES	RS	PI	RV	PR	Lambda	DI	AOI
Panel A: Stock-based measures: Mergers and acquisitions									
TRADE	0.001 (0.015)	0.002 (0.010)	-0.003 (0.010)	-0.001 (0.003)	-0.002 (0.002)	0.003** (0.002)	-0.002 (0.002)	-0.504*** (0.174)	0.002 (0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	4,306	4,306	4,302	4,302	4,111	4,428	4,306	4,385	4,302
Panel B: Stock-based measures: Earnings announcements									
TRADE	-0.002 (0.014)	-0.009 (0.014)	-0.015 (0.014)	0.006* (0.003)	-0.005 (0.004)	0.001 (0.003)	0.001 (0.001)	-0.001 (0.022)	-0.000 (0.004)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	1,101	1,101	1,101	1,101	1,087	1,138	1,101	1,138	1,101
Panel C: Stock-based measures: Other events									
TRADE	-0.017 (0.035)	0.024 (0.020)	0.028 (0.025)	0.005 (0.010)	-0.003 (0.005)	0.001 (0.003)	-0.005 (0.005)	-0.218 (0.343)	0.005 (0.006)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	1,467	1,467	1,467	1,467	1,411	1,489	1,467	1,482	1,467
Panel D: Option-based measures: Mergers and acquisitions									
TRADE	-0.028** (0.013)	0.019** (0.009)	0.004 (0.003)	-0.002 (0.006)	-2.501 (2.770)	0.001*** (0.000)	0.001*** (0.000)	0.000* (0.000)	0.000*** (0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	2,977	2,960	2,977	1,210	2,977	2,977	2,977	2,977	2,977
Panel E: Option-based measures: Earnings announcements									
TRADE	-0.005 (0.010)	0.019* (0.011)	-0.001 (0.004)	-0.003 (0.006)	0.657 (3.817)	0.000** (0.000)	0.000* (0.000)	0.000* (0.000)	0.000*** (0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	1,029	1,029	1,029	605	1,029	1,029	1,029	1,029	1,029
Panel F: Option-based measures: Other events									
TRADE	-0.023 (0.018)	0.042* (0.024)	-0.009 (0.010)	-0.004 (0.013)	4.144 (3.710)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000** (0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	926	861	926	320	926	926	925	926	926

TABLE 12
Conditioning on Information Direction

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 2. In **Panels A and C**, we consider trades related to positive news; in **Panels B and D**, trades related to negative news. 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	ES	RS	PI	RV	PR	Lambda	DI	AOI
Panel A: Stock-based measures: Positive news									
TRADE	0.006 (0.014)	0.005 (0.009)	0.002 (0.009)	-0.001 (0.003)	-0.002 (0.002)	0.004** (0.001)	-0.002 (0.002)	-0.409*** (0.143)	0.001 (0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	5,472	5,472	5,468	5,468	5,264	5,595	5,472	5,549	5,468
Panel B: Stock-based measures: Negative news									
TRADE	-0.062** (0.030)	-0.016 (0.023)	-0.017 (0.023)	0.004 (0.007)	-0.002 (0.003)	0.000 (0.002)	-0.001 (0.003)	-0.177 (0.302)	0.002 (0.005)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	1,402	1,402	1,402	1,402	1,345	1,460	1,402	1,456	1,402
	QSO	IV	IVS	IVSK	LOV	OS	CS	PS	LOS
Panel C: Option-based measures: Positive news									
TRADE	-0.028** (0.011)	0.025*** (0.008)	0.003 (0.003)	-0.002 (0.005)	-1.752 (2.363)	0.001*** (0.000)	0.001*** (0.000)	0.000** (0.000)	0.000*** (0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	3,975	3,894	3,975	1,638	3,975	3,975	3,974	3,975	3,975
Panel D: Option-based measures: Negative news									
TRADE	0.005 (0.014)	-0.005 (0.010)	-0.008 (0.005)	-0.002 (0.008)	1.790 (5.433)	0.000* (0.000)	0.000 (0.000)	0.000* (0.000)	0.000** (0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	957	956	957	497	957	957	957	957	957

TABLE 13
Signed Option Measures

The dependent variables are signed option measures, measured at the company level at time t , over the period 2005-2012. *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 2. **In Panel A**, we include firm and time fixed effects and **in Panel B**, 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.

	OBC	OSC	CBC	CSC	OBP	OSP	CBP	CSP
Panel A: Signed OS Measures with time and firm fixed effects								
TRADE	0.010*** (0.003)	0.006** (0.003)	0.000 (0.001)	0.004** (0.001)	0.003* (0.002)	0.002 (0.002)	-0.000 (0.001)	-0.001 (0.001)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	1,970	1,970	1,970	1,970	1,718	1,718	1,718	1,718
Panel B: Signed OS Measures with time and firm fixed effects (control group adjusted)								
TRADE	0.008*** (0.002)	0.005** (0.002)	0.000 (0.001)	0.003** (0.001)	0.003* (0.002)	0.003* (0.001)	-0.000 (0.001)	-0.001 (0.001)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	1,970	1,970	1,970	1,970	1,718	1,718	1,718	1,718

Supplement to “Chasing Private Information”: Online Appendices

Appendix A Supplement to Section 3

TABLE A1
Monthly Returns and Stock-based Information Measures

The dependent variable is the monthly absolute stock return, $ARET$, compounded daily, measured at the company level at time $t+1$ over the period 1995-2012. All definitions of control variables, measured at the daily frequency, mirror those in Table 2. Standard errors (in parentheses) are clustered at the time dimension. ***, **, * denote 1%, 5%, and 10% level of statistical significance, respectively.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
QS	0.012*** (0.003)								
ES		0.018*** (0.003)							
RS			0.020*** (0.003)						
PI				0.034** (0.013)					
RV					0.268*** (0.061)				
PR						0.613*** (0.055)			
Lambda							0.408** (0.182)		
DI								-0.434*** (0.089)	
AOI									-0.015** (0.007)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	223,994	223,994	223,921	223,919	57,573	223,994	57,573	223,680	223,921

Appendix B Supplement to Section 5

TABLE B2
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 15 prior trading days. All definitions of control variables, measured at the daily frequency, mirror those in Table 2. In Panel A, we consider the baseline specification. Panel B includes firm fixed effects. Panel C additionally includes time fixed effects. While 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.

	QS	ES	RS	PI	RV	PR	Lambda	DI	AOI
Panel A: Baseline estimates									
TRADE	-0.024 (0.028)	-0.001 (0.024)	-0.005 (0.021)	0.006 (0.005)	0.001 (0.006)	0.002 (0.002)	-0.004* (0.002)	-0.269*** (0.096)	-0.000 (0.004)
LNSIZE	-0.272*** (0.057)	-0.272*** (0.054)	-0.214*** (0.044)	-0.051*** (0.008)	-0.057*** (0.007)	-0.011*** (0.002)	-0.019*** (0.003)	0.111 (0.145)	-0.002 (0.006)
LNVOL	-0.008 (0.045)	-0.000 (0.045)	-0.013 (0.040)	0.015** (0.006)	0.035*** (0.007)	0.005*** (0.001)	0.008*** (0.002)	-0.740*** (0.198)	-0.032*** (0.008)
TURNOVER	-7.195*** (2.507)	-5.663** (2.388)	-3.273 (2.042)	-1.707*** (0.350)	0.999** (0.391)	1.144*** (0.117)	-0.685*** (0.118)	8.286 (8.562)	0.444 (0.391)
PRC	0.007** (0.003)	0.004 (0.002)	0.003* (0.002)	0.000 (0.000)	0.002*** (0.000)	0.000 (0.000)	0.000*** (0.000)	-0.003 (0.007)	-0.000 (0.000)
Constant	4.269*** (0.420)	4.239*** (0.365)	3.478*** (0.308)	0.614*** (0.048)	0.359*** (0.035)	0.118*** (0.012)	0.188*** (0.018)	8.827*** (1.454)	0.585*** (0.034)
#Obs	12,950	12,950	12,946	12,946	12,331	13,223	12,950	13,114	12,946
Panel B: With firm fixed effects									
TRADE	-0.013 (0.015)	0.010 (0.011)	0.006 (0.010)	0.003 (0.004)	-0.000 (0.005)	0.002 (0.001)	-0.002 (0.002)	-0.222*** (0.072)	-0.002 (0.004)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	12,950	12,950	12,946	12,946	12,331	13,223	12,950	13,114	12,946
Panel C: With time and firm fixed effects									
TRADE	-0.015 (0.014)	0.015 (0.010)	0.010 (0.010)	0.003 (0.004)	0.003 (0.003)	0.003** (0.001)	-0.002 (0.002)	-0.227*** (0.075)	-0.003 (0.004)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	12,950	12,950	12,946	12,946	12,331	13,223	12,950	13,114	12,946
Panel D: With time and firm fixed effects (control group adjusted)									
TRADE	-0.001 (0.009)	0.003 (0.007)	-0.000 (0.006)	0.002 (0.002)	-0.001 (0.001)	0.003** (0.001)	0.000 (0.001)	-0.216*** (0.076)	-0.000 (0.002)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	12,950	12,950	12,946	12,946	12,331	13,223	12,950	13,114	12,946

TABLE B3
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 15 prior trading days. All definitions of control variables, measured at the daily frequency, mirror those in Table 2. **Panel A** considers a baseline specification. **Panel B** includes firm fixed effects. **Panel C** additionally includes time fixed effects. While 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.

	QSO	IV	IVS	IVSK	LOV	OS	CS	PS	LOS
Panel A: Baseline estimates									
TRADE	-0.005 (0.009)	-0.017 (0.011)	0.006** (0.002)	-0.016*** (0.006)	1.731 (1.699)	0.001*** (0.000)	0.001*** (0.000)	0.000* (0.000)	0.000*** (0.000)
LNSIZE	-0.049*** (0.013)	-0.131*** (0.016)	0.001 (0.001)	-0.006 (0.005)	-6.148*** (1.275)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
LNVOL	0.010 (0.013)	0.080*** (0.015)	-0.000 (0.001)	0.004 (0.005)	-3.741*** (1.226)	0.000* (0.000)	0.000 (0.000)	0.000 (0.000)	0.000* (0.000)
TURNOVER	-3.646*** (0.618)	2.123*** (0.679)	-0.342** (0.148)	0.418 (0.425)	-663.526*** (71.074)	0.019** (0.008)	0.011** (0.005)	0.009** (0.004)	0.012** (0.005)
PRC	-0.003*** (0.001)	0.002 (0.002)	-0.000 (0.000)	0.001** (0.000)	-0.165** (0.069)	0.000** (0.000)	0.000** (0.000)	0.000** (0.000)	0.000** (0.000)
Constant	1.216*** (0.109)	1.257*** (0.117)	-0.008 (0.012)	0.080** (0.039)	181.084*** (10.637)	-0.001 (0.001)	-0.000 (0.001)	-0.001** (0.000)	-0.000 (0.000)
#Obs	9,052	8,949	9,052	4,180	9,052	9,050	9,050	9,050	9,052
Panel B: With firm fixed effects									
TRADE	-0.016*** (0.004)	0.006* (0.004)	0.002 (0.002)	-0.004 (0.003)	-1.757 (1.558)	0.001*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	9,052	8,949	9,052	4,180	9,052	9,050	9,050	9,050	9,052
Panel C: With time and firm fixed effects									
TRADE	-0.015*** (0.004)	0.010*** (0.003)	0.002 (0.002)	-0.004 (0.002)	-1.783 (1.518)	0.001*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	9,052	8,949	9,052	4,180	9,052	9,050	9,050	9,050	9,052
Panel D: With time and firm fixed effects (control group adjusted)									
TRADE	-0.011*** (0.003)	0.009*** (0.004)	0.003 (0.002)	-0.001 (0.003)	-1.280 (1.351)	0.001*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	9,052	8,949	9,052	4,180	9,052	9,050	9,050	9,050	9,052

TABLE B4
Option-based Measures: Non-Strategic Incentives

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 2. **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). 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.

	QSO	IV	IVS	IVSK	LOV	OS	CS	PS	LOS
Panel A: Trade within two days of information acquisition									
TRADE	-0.014 (0.018)	0.015 (0.011)	0.007 (0.004)	-0.004 (0.006)	-3.961 (4.089)	0.001* (0.000)	0.001** (0.000)	0.000 (0.000)	0.000* (0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	1,535	1,530	1,535	734	1,535	1,535	1,535	1,535	1,535
Panel B: Number of same-trader trades less than or equal to 7									
TRADE	-0.033** (0.016)	0.018 (0.013)	0.002 (0.005)	-0.006 (0.005)	-4.606 (3.434)	0.001** (0.000)	0.000*** (0.000)	0.000 (0.000)	0.000*** (0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	2,324	2,309	2,324	1,042	2,324	2,324	2,324	2,324	2,324
Panel C: Number of trades per company less than or equal to 5									
TRADE	-0.009 (0.013)	0.011 (0.011)	-0.004 (0.005)	-0.006 (0.007)	-1.251 (3.086)	0.000** (0.000)	0.000** (0.000)	0.000 (0.000)	0.000** (0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	1,954	1,889	1,954	756	1,954	1,954	1,953	1,954	1,954
Panel D: Number of trades per legal case less than or equal 15									
TRADE	-0.008 (0.013)	0.000 (0.011)	-0.003 (0.004)	-0.002 (0.005)	0.882 (3.144)	0.000** (0.000)	0.000*** (0.000)	0.000 (0.000)	0.000** (0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	2,343	2,328	2,343	1,031	2,343	2,343	2,343	2,343	2,343
Panel E: Profits lower than \$100k									
TRADE	-0.003 (0.012)	0.007 (0.010)	0.004 (0.004)	-0.000 (0.008)	-4.535 (3.592)	0.000** (0.000)	0.000** (0.000)	0.000 (0.000)	0.000** (0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	2,481	2,458	2,481	1,021	2,481	2,481	2,481	2,481	2,481

TABLE B5
Conditioning on the Listing Exchange

The dependent variables are stock-based information measures (in **Panels A-C**) and option-based information measures (in **Panels D-F**), 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 2. In **Panels A and D**, we consider trades of companies listed on NYSE; in **Panels B and E**, trades of companies listed on NASDAQ; in **Panels C and F**, trades of companies listed on all other exchanges. 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	ES	RS	PI	RV	PR	Lambda	DI	AOI
Panel A: Stock-based measures: NYSE									
TRADE	0.001 (0.010)	-0.001 (0.006)	-0.007 (0.007)	0.003 (0.003)	-0.003** (0.001)	0.004** (0.002)	0.001 (0.001)	-0.096 (0.076)	0.000 (0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	1,805	1,805	1,803	1,803	1,748	1,830	1,805	1,826	1,803
Panel B: Stock-based measures: NASDAQ									
TRADE	-0.013 (0.016)	0.007 (0.011)	0.004 (0.011)	0.001 (0.004)	-0.002 (0.002)	0.002 (0.002)	-0.002 (0.002)	-0.395** (0.168)	0.003 (0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	4,645	4,645	4,643	4,643	4,484	4,766	4,645	4,733	4,643
Panel C: Stock-based measures: Other exchanges									
TRADE	0.011 (0.039)	-0.038 (0.049)	-0.031 (0.052)	-0.007 (0.014)	0.003 (0.002)	0.006 (0.006)	-0.015* (0.008)	-1.866 (1.163)	-0.008 (0.010)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	424	424	424	424	377	459	424	446	424
	QSO	IV	IVS	IVSK	LOV	OS	CS	PS	LOS
Panel D: Option-based measures: NYSE									
TRADE	-0.024 (0.019)	0.023* (0.013)	0.006* (0.003)	-0.005 (0.004)	-1.412 (3.722)	0.001*** (0.000)	0.000*** (0.000)	0.000 (0.000)	0.000*** (0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	1,638	1,638	1,638	879	1,638	1,638	1,638	1,638	1,638
Panel E: Option-based measures: NASDAQ									
TRADE	-0.022** (0.011)	0.016* (0.008)	-0.001 (0.004)	0.001 (0.006)	-1.910 (2.763)	0.001*** (0.000)	0.000*** (0.000)	0.000** (0.000)	0.001*** (0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	3,228	3,146	3,228	1,243	3,228	3,228	3,227	3,228	3,228
Panel F: Option-based measures: Other exchanges									
TRADE	0.041 (0.023)	-0.059 (0.032)	-0.011 (0.016)	-0.027 (0.029)	11.261 (11.667)	-0.001 (0.001)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs	66	66	66	13	5 66	66	66	66	66