The Signal Quality of Earnings Announcements: Evidence from an Informed Trading Cartel

Chloe L. Xie
chloex@stanford.edu
Graduate School of Business
Stanford University

November 1, 2019

Working paper and subject to change.

Abstract

This study examines the revealed preference of informed traders to infer the extent to which earnings announcements are informative of subsequent stock price responses. From 2011 to 2015, a cartel of sophisticated traders illegally obtained early access to firm press releases prior to publication and traded over 1,000 earnings announcements. I study their constrained profit maximization: which earnings announcements they chose to trade vs. which ones they forwent trading. Consistent with theory, these traders targeted more liquid earnings announcements with larger subsequent stock price movement. Despite earning large profits overall, the informed traders enjoyed only mixed success in identifying the biggest profit opportunities. Controlling for liquidity differences, only 31% of their trades were in the most extreme announcement period return deciles. I model the informed traders' tradeoff between liquidity and expected returns. From this model, I recover an average signal-to-noise ratio of 0.4. I further explore two potential economic sources of this noise: (i) ambiguous market expectations of earnings announcements and (ii) heterogeneous interpretations of earnings information by the marginal investor. Empirically, I document that the informed traders avoided noisier earnings announcements as measured by both sources of noise.

For their endless erudition and stalwart support, I'm grateful to my trusty advisory committee: Joseph Piotroski (chair), Jungho Choi, Charles Lee, Maureen McNichols, and Jeffrey Zwiebel. I additionally thank Lisa De Simone, Brandon Gipper, David Larcker, Ivan Marinovic, and Kevin Smith for helpful discussions. I am grateful for the training and support from Stanford Graduate School of Business. I thank Wall Street Horizons for providing data. I thank journalist Isobel Koshiw for sharing her contacts and research. I thank Shay Elbaum from Stanford Law School for research assistance. I thank Jim Key from Cision PR Newswire for sharing institutional insights. I thank a long list of employees from the U.S. District Court of Eastern New York, the National Archives, the U.S. Attorneys Offices at the Department of Justice, the U.S. Securities and Exchange Commission, and the U.S. Secret Service. Finally, I extend my sincere gratitude to a group of interviewees who shall remain anonymous in this paper.

1. Introduction

To what extent are earnings press releases informative of the market's stock price responses? This informativeness depends on the signal quality of earnings announcements. To illustrate, consider two levels of signal quality on opposite ends of the spectrum. Suppose earnings announcements are high-quality signals. Investors, upon reading an earnings press release, can accurately predict the market's stock price response. On the other end of the spectrum in which earnings announcements are low-quality signals of stock price responses, investors are surprised by the market's response to earnings because the mapping of the earnings announcement to price reaction is unclear. This question of earnings announcement signal quality is important. In their statement of purpose, the U.S. Securities and Exchange Commission declares that financial disclosures should provide "knowledge for all investors to use to judge for themselves whether to buy, sell, or hold a particular security" and to "make sound investment decisions."[1] The contribution of this paper is to empirically identify and quantify the signal quality of earnings announcements.

The theory literature identifies two economic channels by which earnings may be low-quality signals of stock price responses. First, in the pre-announcement period, markets incorporate into prices an assortment of private information differing in source and precision. As a result, individual investors cannot infer the market's expectation of earnings from prices (Brunnermeier, 2005; Kim and Verrecchia, 1991). Second, earnings announcements are complex, and investors differ in their ability to process the plethora of hard and soft information. At the time of earnings announcements, investors heterogeneously interpret the content in public disclosures, generating large abnormal trading volumes (Kim and Verrecchia, 1994). Both sources of noise may limit the ability of individual investors to understand stock price responses to earnings announcements.

[1] For more information, see https://www.sec.gov/Article/whatwedo.html

To empirically estimate the signal quality of quarterly earnings announcements of US public companies, I examine a natural experiment in which informed investors made predictions of stock price responses to earnings announcements. From 2011 through 2015, an international hacker group illegally obtained access to the servers of three commercial newswire companies. These servers stored hundreds of thousands of confidential firm press releases awaiting dissemination to the public. The hackers sold this illegal access to a cartel of sophisticated investors (e.g. ex-hedge fund managers, asset managers, and more). These investors knew the earnings announcements in advance and profited through informed trade. Using transcripts from court proceedings and Freedom of Information Act (FOIA) requests, I gathered data on 1,029 informed-traded earnings announcements over this five-year period. From the archives of the hacked newswires and Factiva's database, I also gathered the set of 10,100 press releases that were disseminated on the same day via the same newswire. The traders had access to these press releases but forwent trading on them. The informed traders were selective: they chose to trade 9.25% of the illegally obtained earnings announcements.

My empirical strategy is to use the informed traders' performance to recover earning announcement signal quality. The economic intuition is that the profitability of informed traders depends on how well the information in earnings announcements predicts stock price responses to earnings. The empirical test is straightforward: controlling for liquidity, to what extent were these informed traders[2] identifying the earnings announcements with the largest ex-post returns? In other words, how well were these sophisticated traders able to predict stock price responses from their foreknowledge of the content of earnings announcements?

[2] According to definitions in section 10(b)5-2 of the Securities Exchange Act of 1934, because these traders received material nonpublic information knowing that it was obtained by breach of fiduciary duty, they are legally classified as insider traders. However, they are not affiliated with the firms they inside-traded on. Hence, they are not a classic 'insider' such as a CEO or executive. To clearly draw the distinction between a corporate insider and any insider trader as defined by the law, throughout the rest of this paper, I refer to these traders as 'informed traders'. For details on the rules and regulations of insider trading, see https://www.govinfo.gov/content/pkg/FR-2000-08-24/pdf/00-21156.pdf

I use informed trading theory to characterize the constrained optimization problem of the informed traders. The theoretical literature on insider trading (Kyle, 1985; Kyle 1989) makes clear predictions about how profit-maximizing insiders trade. Informed traders make greater profits when (i) the signal differs more from the market's expectation, and (ii) the market is more liquid, decreasing price impact. The informed traders' signal is the earnings announcement and they form expectations about the future earnings announcement return. This expectation is unobservable. I use realized returns as a proxy for the informed traders' expectation of earnings announcement returns. Therefore, I test the joint hypothesis that informed traders choose earnings announcements with greater expected returns and that their expectations are accurate. For the liquidity prediction, I empirically estimate the covariance between measures of liquidity (dollar-volume) and informed trade.

Empirically, I test whether the informed traders behaved in a manner consistent with market microstructure theory. First, on the extensive margin, the informed traders chose more liquid earnings announcements. Compared to the unconditional mean probability of informed trade, a one standard deviation increase in liquidity increases the probability of trade by 50%. Liquidity is especially important in this setting because of detection risk. Large price impact prior to public disclosures bears the risk of discovery. Second, the informed traders chose earnings announcements with larger ex-post returns. A one standard deviation increase in the magnitude of realized stock returns[3] increases the probability of trade by 19%. This finding confirms the joint hypothesis that informed traders could identify, and preferred to trade on, earnings with larger returns. Furthermore, on the intensive margin, the informed traders more aggressively traded earnings announcements with higher returns. Conditional on a stock that is informed-traded, a one percentage point increase in realized stock returns increases the informed traders' price impact by 8.5 bps.

[3] I use the magnitude (absolute value) of stock returns because informed traders were able to take long or short positions, depending on the earnings announcement.

To these informed traders, earnings announcements are noisy signals of stock price returns and the precision of these signals directly affects their ability to "pick the winners." To gauge the quality of their signal, I first non-parametrically compare the informed-traded earnings announcement returns to a liquidity and time-matched sample. I find that the density of informed-traded earnings announcement returns is flatter (i.e., has greater kurtosis, or fatter tails) than that of the non-traded sample. This flatness reflects the ability of the informed traders to choose earnings announcements with larger stock price returns. This flatness is a robust feature of the data. Within each quintile of liquidity, informed traders choose earnings announcements with larger realized returns. Their performance is statistically significantly greater than that of random choice. However, the difference is economically small. For example, only 31% of earnings announcements traded by the informed traders fell within the tail deciles. About 70% of their informed trades missed the biggest stock price return opportunities. They traded earnings announcements with an average absolute return of 5.15%. The average earnings announcement return in the tail deciles is 11.3% (median 9.2%).

To estimate signal noise from performance, I formulate a model of informed trade. In my model, an investor receives an array of noisy private signals about announcement period returns. The investor seeks to maximize profit by choosing to trade earnings announcements that are liquid and have large returns. The investor's ability to do so depends on the precision of his return signals (i.e., the earnings announcements). I estimate my model using simulated method of moments (SMM), where my moments are average returns, liquidity and their interaction. Using these moments, I recover parameter estimates that imply informed traders were willing to forgo one percent of expected return in exchange for 0.65 standard deviations of liquidity. Their performance implies a low signal-to-noise (SNR) ratio of on average 0.4. Within the context of this natural experiment, this is a causal estimate: signal quality determines performance. For comparison, I consider a simple benchmark trading strategy based on earnings surprise. This benchmark yields a comparable SNR estimate of 0.42. I infer from these low signal-to-noise ratios that earnings announcement press releases are poor signals of subsequent stock price responses.

To contextualize this finding, I provide some cross-sectional evidence of economic channels that give rise to signal noise in earnings announcements. Specifically, I explore two potential types of uncertainty the informed traders faced. Kim and Verrecchia (1991, 1994, 1997) pinpoint two dimensions of information uncertainty earnings announcement traders face: that of market expectations in the pre-announcement period and that of heterogeneous interpretations in the announcement period. In the first instance, the informed traders do not know how much of each earnings announcement the market has already priced (i.e., *ex-ante* uncertainty). In the second, they do not know how the marginal investor will interpret the information content upon its publication (i.e., *ex-post* uncertainty). I construct proxies of these two types of information uncertainty and test whether these sources of signal noise negatively covary with the stock picks of the informed traders. I hypothesize, and indeed find, that the informed traders avoided noisier earnings announcements, as measured by both *ex-ante* and *ex-post* uncertainty.

Specifically, I construct two empirical proxies of the *ex-ante* uncertainty (ambiguity about market expectations). First, I examine analyst forecast disagreement. When analysts differ in their forecasts of expected earnings and revenue, there is more pre-announcement private information. Empirically, I find that a one standard deviation increase in analyst disagreement is associated with a 22% decrease in the probability of informed trade, compared to the unconditional mean of informed trade of 9.25%. Second, I examine an earnings announcement's proximity to that of a peer firm. Due to information spillovers, more of a firm's earnings announcement is likely to be priced when it follows a comparable firm's earnings announcement. I find that the informed traders are 19% less likely to trade on an earnings announcement that is within two weeks after that of another firm in the same 4-digit SIC code.

I also construct two empirical proxies of the *ex-post* uncertainty (noise due to heterogeneity in investor interpretation of information). First, I examine directional disagreement in earnings and revenue surprise. Controlling for the average surprise, if earnings surprise conflicts in direction with revenue surprise, then there is more scope for heterogeneous interpretations. Empirically, I find when signals for earnings and revenue are in the same direction, informed trade is 40% more likely. Second, I examine whether managerial guidance confirms analyst expectations. Managerial guidance can range from soft information, such as forward-looking statements, to quantitative information that is directly comparable to analyst forecasts. Interpretations of soft, qualitative information may be more dispersed compared to interpretations of quantitative guidance relative to analyst expectations. I find that informed trade is 25% more likely to occur for earnings announcements in which managers confirm analyst forecasts.

An important threat to the generalizability of this setting is the illegality of informed trade. The informed traders faced detection risk but whether detection risk is a threat to identification is less obvious. In Section 6, I provide additional analyses to rule out the concern that detection risk may be have affected how the traders allocated their capital. I provide evidence that despite the risk of high detection costs, the informed traders' objective was still to identify and trade on earnings announcements with the largest stock price reactions. The informed traders primarily managed detection risk by limiting shares traded and the number of earnings announcements they traded. Avoiding detection is not a threat to the empirical identification insofar as the informed traders' management of detection risk does not affect their objective to "pick the winners."

This unique natural experiment reveals a general fact that earnings announcements are noisy signals of subsequent market reactions. The informed traders had "perfect foresight" from stolen earnings announcement press releases, but they were only able to enjoy mixed success in predicting next-day stock returns. Their poor performance implies that capital market participants have difficulty mapping earnings information to stock price reactions. The contributions of this paper are to empirically quantify the limited informativeness of quarterly earnings announcements to individual investors, provide evidence on the likely sources of signal noise, and shed light on how this noise affects the behaviour of capital market participants.

I elaborate on these contributions in relation to three strands of extant literature in the next section. Section 3 discusses details of the empirical setting including institutional background, data collection, measure construction, and summary statistics. Section 4 presents the research design to test for earnings announcement signal quality and confers the main empirical findings of this study. Section 5 further explores the main finding in cross-sectional tests of signal noise. Section 6 addresses primary concerns regarding the identification assumption and empirical robustness. Section 7 concludes.

2. Related Literature and Contributions

In this section, I discuss the three areas of economic research that are the most pertinent to this study. Primarily, this paper endeavours to understand the signal quality (or noise ratio) of earnings announcements. These signals are impounded in equity prices: a broad literature studies earnings announcement returns. I lean on this literature to motivate my research question and contextualize my results. Secondly, the empirical setting by which I study earnings announcements heavily draws from the literature on insider trading. I depend on insider trading theory to validate the identifying assumption and assess the performance of the informed traders. Finally, the research on financial reporting environment theorizes and empirically studies drivers of noise in earnings announcement returns. This noise poses a challenge to informed traders who are trying to identify the most profitable earnings announcements to trade. I rely on this group of studies to inform my hypotheses regarding the source of noise in earnings announcements.

2.1 Earnings Announcement Returns

This study is nested within a larger literature on the extent to which earnings announcements are useful. For decades, this research question focused on whether accounting income *numbers* explain stock price returns. Ball and Brown (1968), Ball and Kothari (1991), Campbell et al. (1997), among a rich set of studies, find that stock market returns react to unexpected earnings. In recent years, the literature has expanded from just the earnings numbers to consider *other* dimensions of disclosure. For example, Davis et al. (2012) analyse the linguistic tone of earnings press releases. Henry (2008) conducts rhetorical analyses of press releases to show that document structure, textual complexity, and other linguistic styles influence investors across all levels of sophistication.

More recently, a number of papers have sought to take the earnings announcement *event* in total and compute how much explanatory power it provides of the quarterly stock return variance. Ball and Shivakumar (2008) regress calendar-year returns on their four quarterly earnings announcement returns and find that the R^2 is between 5% and 9%. They conclude that this reflects the total amount of incremental information quarterly earnings announcements bring to the market. Using a philosophically similar approach (i.e. decomposition exercise), Beyer et al. (2010) regress calendar-quarter returns on voluntary and mandatory disclosure events and find that earnings announcements provide 8% of the accounting information driving the quarterly stock returns. While Ball and Shivakumar (2008) and Beyer et al. (2010) then draw qualitatively different conclusions[4], both papers agree that earnings announcements provide little new information to equity markets.

On the other hand, a number of studies document that the informativeness of earnings announcements, as proxied by the market response to earnings announcements, has increased overtime (Landsmand and Maydew, 2002; Francis et al., 2002; Collins et al., 2009; Beaver et al., 2018). Not only have earnings announcements increased in length (Francis et al. ,2002), they

[4] Both papers find evidence that most of the information contained in earnings announcements is already reflected in prices prior to the information event. Ball and Shivakumar (2008) interpret this as earnings announcements being uninformative. Beyer et al. (2010) point out that the informativeness characteristic is not as limited as Ball and Shivakumar suggest - "it is not correct to interpret this result as implying that earnings announcements are not relevant (Ball and Shivakumar, 2008). For example, earnings still are likely to play an important disciplining role on management, thus making management forecast credible and, hence, informative."

have dimensionally expanded to include financial statements (Collins et al., 2009), managerial forecasts (Lee and Zhu, 2019) and other concurrent disclosures (Beaver et al., 2019).

This study contributes to this collective understanding by examining earnings announcement informativeness from the perspective of individuals with perfect foresight of the earnings signal. Pankoff and Virgil (1970), in contemplating the meaning of financial statement usefulness, suggest that "the answer to this question lies with the user". In their paper, they propose that an ideal experiment "could be so designed that demand for an information item is measured by the extent to which the item is used as an input for decision-making." Albeit half a century later, this paper precisely identifies one such natural experiment.

2.2 Insider Trading

The empirical setting of this study is an insider trading market microstructure. In this natural experiment, I use the revealed preference of informed traders to reverse-engineer the signal quality of earnings announcements. The novelty of this natural experiment is the cross-section of stocks: the informed traders choose which earnings announcements to trade. First, I ascertain that the informed traders are making choices consistent with theory. From informed trading theory, I hypothesize that the traders choose earnings announcements with more surprising signals and greater liquidity. From the standpoint of the literature, this study provides new evidence that characteristics theorized and empirically proven to accompany insider trading also appertain in the cross-section, and not just in ad hoc cases or in the time series. Below I discuss works that this study (i) refers to in assessing the traders' performance and (ii) contributes to by providing cross-sectional evidence.

Perhaps the two best-known works on information-based asset pricing are Kyle (1985) and Grossman and Stiglitz (1980). Both papers analyse how informed traders strategically trade on their private signals in the presence of noise traders. In Kyle (1985), a single, risk-neutral agent observes the fundamental value of an asset and trades on this private information. The core revelation is that this agent recognizes and manages his price impact. His trades are partially obfuscated by noisy order flows. He will buy (sell) the asset until the expected marginal profit of holding one more (less) share is offset by the price impact of the purchase (sale). In Grossman and Stiglitz (1980), *n* risk-averse agents endogenously choose whether to acquire private information and submit menus of price-quantity pairs whereas in Kyle (1985), the private information is exogenously endowed. The empirical setting is more closely aligned to the Kyle informed trading models. A small group of informed traders have private access to all earnings announcements. They had access to whole newswires at given points in time. The informed traders chose which earnings announcements to trade, not which ones to gain access to.

Kyle (1985) – and a series of Kyle-esque models[5] – yield important insights into how insider traders maximize profit. The insider trades off quantity with price impact. This trade-off is common across a variety of insider trading models. Examples include insider trading models with different types of noise traders (e.g., Admati and Pfleiderer, 1988), public disclosure (e.g., Diamond and Verrecchia, 1987), and portfolio restrictions (e.g., Dow and Gorton, 1995). The constants in these models of asymmetric information are the insider objective, which is always to maximize profit or utility, and the insider's constraint, which is always to minimize cost be it through information, detection, or risk aversion. In Section 4.1, I hypothesize and verify that the informed traders are more likely to trade on an earnings announcement when there is greater surprise, liquidity, and time to trade.

Though the focus of this paper is earnings announcement signal quality, the empirical setting is informed trading. Therefore, this study contributes to several strands of the insider trading literature. *Firstly*, to the best of my knowledge, this is the first paper to empirically analyse insider traders' decision making with respect to private information quality. Previous literature focuses on the price system efficiency and market consequences of insider trading. For example, Meulbroek (1992) studies whether the stock market detects illegal insider trading and

[5] For example, Glosten and Milgrom (1985), Easley and O'Hara (1987), Admati and Pfleiderer (1988) among others. These seminal works analyze trades with asymmetric information and form the basis of how we understand insider traders to behave.

quickly impounds the information. Piotroski and Roulstone (2004) provide evidence of insider trading improving price discovery. Akey et al. (2019) use the same empirical setting in this paper to study market efficiency and test measures of informed trading.

The primary difficulty with studying ex-ante choice is a lack of empirical opportunity: insider traders are usually confounded with the firm. In my empirical setting, I have informed traders choosing across a variety of earnings announcements. This cross-section enables me to control for firm fixed effects. Within the literature, cross-sectional studies of informed trading are sparse. A notable exception is Kacperczyk and Pagnotta (2019) on the economic consequences of asymmetric information. They analyse panel data involving 5058 trades in 615 firms over a ten-year period. Their cross-section differs from the one in this study, however. In their data, the insiders (manually identified via 453 SEC investigations) are still confounded with the information/firms. An example they give in their paper is a hedge fund manager who inside-trades on information acquired through a personal relationship with a firm's CFO. Following this example, an analogy of how the setting in this study complements that of Kacperczyk and Pagnotta (2019) is if they were to study a hedge fund manager who (a) is friends with dozens of CFOs, (b) had acquired the same type of information from all of them, and (c) repeats this illicit behaviour frequently. To that end, the *second* contribution of this study is to provide cross-sectional evidence of insider trading characteristics that are robust to firm fixed effects.

Thirdly, this paper adds to a small group of papers that directly examine cases where the existence of private information is unequivocal and its utilization by insiders is certain. For example, Cornell and Sirri (1992) analyse a 1982 case where insider trading occurred around Anheuser-Busch's tender offer for Campbell Taggart. Koudijs (2015, 2016) study the flow of private information in the 18th century using data on weather which impacted boats sailing between London and Amsterdam. Ahern (2017) analyses the interpersonal relationships of insider trading networks using hand-collected data that covers 1,139 insider tips shared by 622 traders. Precisely pinpointing private information is difficult, but important for the study of informed trade.

2.3 Earnings Announcement Information Environment

Kim and Verrecchia (1991, 1994, 1997) consider two types of information that generates trading volume around earnings announcements. First, KV (1991) focuses on information *in anticipation of* an earnings announcement. In the pre-announcement period, traders are heterogeneously informed. Given their different priors, when a public disclosure (e.g. earnings announcement) takes place, these traders react differently to the announcement which leads to trade. Second, KV (1994) focuses on information *in conjunction with* an earnings announcement. KV (1994) explains that market participants diverge in level of expertise in processing a public disclosure into private information. Public disclosures, such as earnings announcement press releases, could lead to different interpretations by individual investors. KV (1997) combines both types of private information in a model of rational trade. The authors contend that the choice to include both is because, realistically, markets operate with both pre-announcement private information and event-period private information. I concur with their position and consider how each of these two types of private information manifests intuitively in my empirical setting.

I lean on these papers and additional works (Grundy and McNichols, 1989; Holthausen and Verrecchia, 1990; Indjejikian, 1991; Harris and Raviv, 1993; McNichols and Trueman, 1994; Abarbanell et al., 1995) to impose structure on the informed traders' problem. Their problem is two-fold: first, they face uncertainty in the extent of the pre-announcement private information. Informally, they are unsure of how informed they truly are. The private signals they have may be 'priced out' to varying extents. Second, they face uncertainty in the event-period private information. Given the inevitable differences of opinion among traders, how the market will aggregate the information may differ from the informed traders' expectation. Both types of private information diminish the value of these stolen press releases to the informed traders.

3. Empirical Setting: Data and Measures

3.1 Traders with Early Access to Earnings Announcements

From early 2011 to 2015, an international ring of hackers breached the servers of commercial newswire companies (PR Newswire, Marketwired, and Business Wire). Firms depend on these commercial newswire companies to fairly disseminate press releases. These hackers used a variety of methods to "backdoor" into the newswires' servers to access confidential press releases prior to their publication. These hackers sold access to a cartel of sophisticated investors who inside traded on the stolen financial disclosures.[6]

Former SEC Chair Mary Jo White describes this in an official press release:
"This international scheme is unprecedented in terms of the scope of the hacking, the number of traders, the number of securities traded and profits generated… These hackers and traders are charged with reaping more than $100 million in illicit profits by stealing nonpublic information and trading based on that information."

Official investigations are still ongoing at the time of this paper. At least thirty different individuals and entities have reached settlements with the SEC. At least two individuals have been found guilty and sentenced. In *United States v. Vitaly Korchevsky et. al.*, the prosecution documents illegal inside trade for 1,029 earnings announcements.

This empirical setting fits the criteria of the ideal experiment. The economic agents are sophisticated market participants, including hedge fund managers and a former Morgan Stanley portfolio manager. The informed traders had financial incentive to accurately predict earnings announcement returns because they invested their personal capital. They had access to a cross-section of earnings announcements. Furthermore, their trading was constrained. Despite having access to many earnings announcements, the investors were selective in their trades. The 1,029 earnings announcements were chosen from a choice set of 10,100 earnings announcements. Due to limited capital and detection risk, the investors were constrained in the number of earnings

[6] See appendix B for a detailed discussion of the institutional details underlying the empirical setting.

announcements they could trade on. Therefore, their trades are informative of their predictions of stock price responses to earnings announcements.

The empirical strategy is to infer earnings announcement informativeness about stock price returns from the performance of the inside traders. Section 4 details the implementation of this empirical strategy.

3.2 Data Sources

In this section, I describe the data sources used for this project. Through various FOIA requests and by scraping PACER filings, I gained access to the inside trades in the case of United States v. Vitaly Korchevsky et. al. Assembly of the sample begins with 1,029 earnings announcements known to be traded on by the informed traders.

Using the press release title, date, and distributing newswire, I download the full text of press releases from Factiva and the newswire press release archives. In addition to the inside-traded earnings announcements, I gather the full text of press releases of all other earnings announcements published on the same date and by the same newswire. These are the earnings announcements that the informed traders had access to but chose not to trade on. In total, I have 1,029 traded earnings announcements and 10,100 not traded-on earnings announcements. These form the dataset, referred to from now on as the sample.

Next, I gather data from several sources to study the characteristics of these firms, earnings announcements, stocks, and market conditions. From the text of the press releases, I scrape each firm's NYSE or Nasdaq ticker symbol. I match these tickers to GVKEY in the CRSP database and manually check for accuracy using company name. Using CRSP price data, I compute stock return measures. From Compustat, I gather firm balance sheet variables. From Wall Street Horizon, I collect the earnings announcement date and time. deHaan et al. (2015) documents that Wall Street Horizon has the most accurate and comprehensive coverage of earnings announcement times. I cross check these dates and times against I/B/E/S and the textually scraped timestamps from the press releases. From I/B/E/S, I gather other earnings-related parameters such as guidance, analyst coverage, and long-term forecasts. From WRDS Intraday Indicators, I collect equity prices at 9:30 AM, 1:00 PM and 4:00 PM ET. Further, I collect qualitative and quantitative information from reading court transcripts and conducting interviews with parties involved in the case.

3.3 Core Measures: Return and Liquidity

Return

Earnings announcement returns are defined to best fit the trading of the informed traders. For the median inside trade, the position is opened 2 hours prior to the public distribution of the earnings announcement and closed within 20 hours. Earnings announcement return is computed using intra-day prices that match the holding period and time of public disclosure.

If the earnings announcement took place between 1:00 PM ET to post-market (12:00 AM ET):

$$R_{i,t,\tau} = \log\left(\frac{P_{i,t+\tau,Open}}{P_{i,t,1pm}}\right) \tag{1}$$

where $R_{i,t}$ is the earnings announcement return for firm i, trading day t (day of the earnings announcement) and held for τ days[7]; $P_{i,t+\tau,open}$ is the stock price at market opening for τ trading days after the earnings announcement; $P_{i,t,1pm}$ is the stock price at 1:00 PM (before the earnings announcement became public). This is the most common earnings announcement time window: 54% of the sample traded earnings announcements occurred after 1:00 PM (including the post-market window). For example, if an earnings announcement became public at 4:01 PM ET, the return window takes the stock price at 1:00 PM as the beginning price and the market open price the subsequent day as the close-out price.

If the earnings announcement took place pre-market (12:00 AM until 09:30 AM ET):

[7] If the holding period is less than 24 hours, then $\tau = 1$. If the holding period is between 24 hours and 48 hours, then $\tau = 2$. If the holding period is between 48 and 120 hours, then $\tau = 3$.

$$R_{i,t,\tau} = \log\left(\frac{P_{i,t+\tau,Open}}{P_{i,t-1,1pm}}\right) \quad (2)$$

This is the second most likely scenario, covering 45% of the sample earnings announcements.

Liquidity

The informed traders generated price impact in executing their trading strategy. Ideally, with precise trading time and quantity, I would be able to precisely estimate price impact. Despite this data limitation, I may coarsely measure the price impact of informed traders as the equity return during their trading window. For the most common earning announcement time (post-market), I measure the price impact as the return from 1:00 PM to 4:00 PM ET:

$$\rho_{i,t} = \log\left(\frac{P_{i,t,4pm}}{P_{i,t,1pm}}\right) \quad (3)$$

This measure on average overestimates price impact because all informed trade during this window is attributed to the informed traders.

Two important controls related to price impact include asset liquidity and time to trade. Earnings announcements differed by liquidity of underlying asset and upload time to the servers. Both are important for the informed traders. More liquid stocks allow the informed traders to make larger trades with less price impact. More time to trade enables the informed traders to spread out their trades amongst noise/liquidity trades of other investors. Liquidity is measured as the log of average dollar trading volume for the 20 trading days leading up to the earnings announcement window (3 days prior to announcement):

$$L_{i,t} = \ln\left(\frac{1}{20}\sum_{\tau=4}^{23} v_{i,t,-\tau}\right) \quad (4)$$

Since I do not directly observe when the public disclosures are uploaded to the servers for all earnings announcements, I proxy for time to trade using the timing of the public disclosure. Informed traders are likely to have the greatest number of trading hours by which to build their positions when the earnings announcement is near market close. Therefore, the proxy is a dummy variable equal to 1 if the earnings announcement is released in the hour immediately following market close (4:00 PM – 5:00 PM ET) and 0 otherwise.

3.4 Summary Statistics

These earnings announcements are summarized in Table 1. Data on these inside trades were aggregated at the event level, reporting the profit/loss (PL) and dollars traded by press release. Panel A documents that the informed trading tended to concentrate on earnings announcements released in the hours after market close. The earnings announcements that were announced just after market close gave the informed traders the most time to spread out their trades. The informed traders preferred the Fama-French 10 factor industry of business equipment (computers, software, and electronic equipment) over others. Compared to the control sample of earnings announcements where about 1/5 of firms are in the business equipment industry, about 1/3 of inside trades fall in this industry. Panel B presents the full industry breakdown of the informed trades alongside the control sample. Panel C presents summary statistics of earnings announcement characteristics and their covariance with inside trade. Inside-traded earnings announcements tended to have larger stock price responses, more surprising EPS and revenue disclosures, more analyst coverage, greater liquidity, and bundled guidance. See appendix A for precise variable definitions.

The summary statistics about the trading strategy of the informed traders is summarized in Table 2. The non-traded sample consists of 10,100 earnings announcements (Panel A) that were published on the same days and via the same newswires as the informed-traded earnings announcements. Informed traders had a median time to trade of about two hours (Panel B). For 80% of informed earnings announcement trades, the traders opened and closed their position with an average holding period of one day. For the remaining 20%, the informed traders held long-lasting positions (greater than five days). For these trades, the PL and dollars traded data are less applicable to the earnings announcement and therefore excluded from the summary statistics. However, these inside-traded earnings announcements are within the empirical analysis.

4. Research Design and Empirical Results

The research design identifies the informativeness of earnings announcements through the constrained optimization of the informed traders. The informed traders sought to maximize profit subject to price impact, capital constraints, and detection risk. Profit is stock price return multiplied by quantity traded. The informed traders form expectations of future stock price returns to earnings announcements. The accuracy of these expectations depends on the informativeness (i.e. signal quality) of earnings announcements. The quantity traded depends on price impact, capital constraints, and detection risk. Canonical models of informed trade emphasize the price impact constraint (Kyle, 1985; Kyle 1989). Trading greater quantities increases price impact, revealing the private information. Similarly, capital constraints limit the size of positions the informed traders may take. For 30% of informed trades, they used options because of capital constraints. Detection risk constrains the informed traders in the number of earnings announcements traded on and the size of positions taken (see Section 6.1). Subject to these constraints, the quality of the earnings signal determines the propensity by which the informed traders pick the earnings announcements with the largest stock price returns.

Empirically, I test the two core predictions of the informed traders' constrained optimization problem. First, I test whether informed traders choose earnings announcements for which they expect larger earnings announcement returns. A challenge is that I do not directly observe their expectations. However, I can use realized returns as a proxy for their expected return. The power of this proxy depends on the accuracy of their expectations. Therefore, I am testing the joint hypothesis that their expectations are accurate and that they trade earnings with large expected stock price returns. Second, I test whether the informed traders choose earnings announcements where they can trade higher quantities. I construct two proxies for quantity constraints: measures of stock liquidity and time to trade.

After estimating the covariance between returns and liquidity with informed trade, I assess the performance of the informed traders. To what extent did the informed traders succeed in trading the earnings announcements with the largest realized returns? I use the performance of the informed traders as an empirical moment to structurally estimate my model of informed trade. The model quantifies the informed traders' performance into a signal-to-noise ratio. The signal-to-noise ratio measures the informativeness of earnings announcements for subsequent realized returns. For comparison, I benchmark the informed traders' signal-to-noise ratio against that of a simple trading strategy based on earnings surprise.

4.1 Profit Maximization

The seminal informed trading models of Kyle (1985, 1989) propose two major determinants of informed trader profit: (i) how surprising his private information is to the market and (ii) the liquidity of the asset. I test whether the earnings announcements chosen by informed traders tend to have greater realized returns and liquidity. To empirically measure the covariance between the informed traders' choice of earnings announcements to trade and realized returns, I estimate a Logit model. I use a Logit regression model because the trading strategy is binary (trade or not trade) with respect to the sample of earnings announcements. Furthermore, the Logit regression model enables me to include time and industry fixed effects to mitigate the concerns of omitted variable bias.

Define Y_{it} to be an indicator equal to 1 if the earnings announcement of firm i for quarter t is traded by the informed traders and 0 otherwise. The set of explanatory variables includes the absolute value of realized earnings announcement return ($|R_{i,t}|$), liquidity ($L_{i,t}$), and announcement time ($T_{i,t}$). Return and liquidity are winsorized at the 1% level. I take the absolute value of returns because the trade indicator encompasses both short and long positions. The Logit model to be estimated through maximum likelihood is

$$\Pr(Y=1)=\frac{1}{1+e^{-W_{i,t}}} \tag{5}$$

$$W_i=\alpha+\beta_1|R_{i,t}|+\beta_2 L_{i,t}+\beta_3 T_{i,t}$$

Standard errors are clustered by quarter to correct for correlation amongst unobservables within the same earnings season.

Table 3 Panel A presents the results: column (1) is the baseline specification with no fixed effects, column (2) includes time fixed effects (quarter dummies), and column (3) includes time and industry fixed effects (Fama-French 10 portfolio industries). For ease of interpretation, I standardize all non-dummy explanatory variables such that one unit is a standard deviation and compute the at-means marginal effects. In the baseline specification, a one standard deviation increase in earnings announcement returns increases the probability of trade by 1.76 percentage points. Compared to the unconditional probability of inside trade of 9.25%, this effect is economically significant: a 17% increase in probability of trade. Using their early access to earnings announcements, the informed traders are successfully predicting which announcements have higher returns. This covariance between their trading strategy and future returns is robust to time and industry fixed effects.

The informed traders tend to trade more liquid stocks and earnings announcements where they had more time to trade. A one standard deviation increase in pre-announcement dollar volume is associated with a 4.6 percentage point increased probability of informed trade. Relative to the mean probability of informed trade, this is a 50% increase in probability of informed trade. The large preference of informed traders for liquidity may be due to both price impact and discovery risk. Liquidity decreases the price impact of informed trade which increases the profitability of private information. More liquid stocks allow informed traders to trade more quantity and earn greater profits. As in the classic informed trader settings, price impact limits the ability of informed traders to profit from private information. Furthermore, in this setting, the informed traders may be particularly sensitive to price impact because of detection risk.

If the earnings announcement occurred in the hour immediately following the close of markets (4:00 PM – 5:00 PM ET), then the informed traders had the greatest amount of time to trade. Informed traders are 7.85 percentage points more likely to trade an earnings announcement released in the hour after markets close. Relative to the mean probability of informed trade, this is an 85% increase in the probability of informed trade.

The covariance between trading strategy and earnings announcement returns nonlinearly increases with the level of returns and liquidity. Table 3 Panel B illustrates the nonlinearity in the marginal effect of a one standard deviation increase in returns. At low levels of returns and liquidity (10th percentile, column (1)), a one standard deviation increase in returns has a small marginal effect on probability of trade (0.67 percentage points). At high levels of returns and liquidity (90th percentile, column (4)), a one standard deviation increase in returns has a large marginal effect on the probability of trade (3.69 percentage points). The marginal effect of earnings returns is more than five times as large when moving from the 10th to 90th percentile of returns and liquidity. This nonlinearity illustrates the selectiveness of informed traders. Out of many earnings announcements the informed traders are trying to select the most profitable announcements to trade.

To assess the trading strategy along the intensive margin, I subsample to only the earnings announcements that the informed traders chose to trade. I measure the intensity of trade by informed traders using the pre-announcement price impact ($\rho_{i,t}$). Price impact is measured as the change in price for the period of informed trading prior to the earnings announcements (1:00 PM – 4:00 PM ET). Conditional on trading the earnings announcement, is price impact larger when returns are larger? To measure this covariance, I estimate the following OLS regression model of price impact.

$$\rho_{i,t} = \alpha + \beta_1 R_{i,t} + \beta_2 L_{i,t} + \beta_3 TT_{i,t} + \epsilon_{i,t} \tag{6}$$

Table 4 presents the results with the same fixed effects by column as in Table 3 Panel A. Standard errors are clustered by quarter. An important difference is that realized returns are expressed in percentage points, not units of standard deviation. The informed traders predicted and more aggressively traded earnings announcements with larger returns. The price impact is 8.5 bps larger for every additional percentage point of earnings announcement return. The informed traders had smaller price impact on more liquid stocks and larger price impact for earnings announcements they had more time to trade. These findings along the intensive margin corroborate the consistency of the trading strategy with informed trading theory.

4.2 Inside Trader Performance

Although the informed traders behaved in a manner consistent with the theory of informed trading, their performance was surprisingly poor. Controlling for liquidity, the informed trades were within the top or bottom decile of earnings announcements about 30% of the time. The informed traders struggled to identify the earnings announcements with the largest returns. This poor performance reflects the noisiness of earnings announcements as a predictor of stock price responses. Despite knowing the earnings announcements in advance, the informed traders had difficulty identifying the ones with the largest returns.

To control for liquidity, I take two approaches: (i) matching and (ii) splitting the sample into quintiles of liquidity buckets. For the first, I match each earnings announcement to the three earnings announcements within the same week with the most similar liquidity (month-prior dollar volume). Using this liquidity-matched sample, I measure the performance of the informed traders by their ability to identify earnings announcements in the top and bottom deciles of return. The kernel density estimator is the Epanechnikov (optimal mean square error kernel) with bandwidths of 0.57 percent (inside-traded) and 1.17 percent (non-traded). The distribution of earnings announcements returns for the inside-traded sample is more dispersed than that of the non-traded sample. For the joint sample, the bottom decile is a return of -6.16% and the top decile is a return of 6.32%. The non-traded sample has 17% of its mass in the bottom and top deciles, while the inside trade sample has 28% of its mass in the bottom and top deciles. The 11% difference is statistically significant at the 1% level. However, the difference is surprisingly small. Despite knowing the earnings announcements in advance, 72% of the inside trades fall between the top and bottom deciles of returns.

For the second approach, I sort the sample of earnings announcements into quintiles of liquidity for each quarter. Figure 2 Panel B plots five distributions of earnings announcement returns for the non-traded and traded samples. For each Epanechnikov kernel density plots, the distribution of earnings announcement returns for the informed-traded sample is more disperse than that of the non-traded sample. The fraction of mass in the bottom and top deciles varies from 30% to 36% for informed-traded earnings announcements by liquidity quintile. For each quintile, the informed-traded mass in the tails is statistically significantly greater than that of the non-traded sample at the 1% level.

4.2.1 Model Setup

Using a model of informed trade, I quantify this performance metric in terms of how noisy earnings announcements are as a signal of stock price responses. For each period t, there are N_t earnings announcements enumerated $i = 1, \dots, N_t$. There is a trader who receives a noisy private signal about each earnings announcement stock return:

$$s_i = R_i + \epsilon_i \tag{7}$$

where R_i is the earnings announcement stock return and $\epsilon_i \sim N(0, \sigma_\epsilon^2)$ is mean-zero, normally distributed noise with variance σ_ϵ^2. The profit from trading earnings announcement i is a function of the earnings announcement return (R_i) and asset liquidity (L_i). I parameterize this profit function using a first order polynomial approximation:

$$\pi_i(R_i, L_i) = \beta_1 R_i + \beta_2 L_i + \beta_3 R_i L_i \tag{8}$$

For each period, the informed trader chooses whether to trade the earnings announcements ($X_i = 1$) or not to trade ($X_i = 0$) subject to the constraint of trading a total of $X_t = \sum_i X_i$ earnings announcements. I assume that the informed trader is risk neutral and maximizes expected profit

$$\pi = \sum_i E[\pi_i(R_i, L_i)|s_i]X_i \quad (9)$$

The informed trader chooses the earnings announcements with the greatest expected profit conditional on his signal ($E[\pi_i(R_i, L_i)|s_i]$) until he reaches the trading constraint X_t. The informed trader knows the liquidity (L_i) of each earnings announcement but has a noisy conditional expectation of earnings returns ($E[R_i|s_i]$).

4.2.2 Model Identification and Estimation

I estimate my model for each quarter of the data where there are at least 10 informed trades.[8] For each quarter, I have data on realized earnings announcement returns, whether the informed trader chose to trade on the earnings announcement, and an empirical proxy for liquidity. What I do not observe includes the signals that the informed trader received and the coefficients on the profit function ($\beta_1, \beta_2, \beta_3$). The informed trader processes the information in the earnings announcement press releases to form an expectation of the stock price response. Latent in this expectation is a noisy signal of future stock price response. The key parameter of interest is the noisiness of the earnings announcement signal (σ_ϵ^2).

The informed trader chooses the earnings announcements with the greatest expected profit. Since I cannot directly observe informed trader profits, I standardize the profit function such that ($\beta_1 = 1$). This standardization results in a natural interpretation of the coefficient on liquidity (β_2) as the profit maximizing tradeoff between one percent of expected return and one unit of liquidity. Similarly, the coefficient on the interaction between returns and liquidity (β_3)

---

[8] I exclude quarters for which the informed traders had intermittent access to newswires and traded less than 10 earnings announcements.

may be interpreted as the profit maximizing tradeoff between one percent of expected return and one unit of expected return multiplied by liquidity. I assume that the informed trader has a prior that earnings announcement returns are normally distributed with mean (μ_R) and standard deviation (σ_R) estimated from the data. Over the sample, the mean is approximately zero and standard deviation is ($\sigma_R = 5.6\%$). The informed trader's expected earnings announcement conditional on signal s_i is

$$E[R_i|s_i] = \frac{\sigma_R^2}{\sigma_R^2 + \sigma_\epsilon^2} s_i \tag{10}$$

Therefore, the expected profit of trading earnings announcement i is

$$E[\pi_i(R_i, L_i)|s_i] = \frac{\sigma_R^2}{\sigma_R^2 + \sigma_\epsilon^2} s_i + \beta_2 L_i + \beta_3 L_i \left(\frac{\sigma_R^2}{\sigma_R^2 + \sigma_\epsilon^2} s_i \right) \tag{11}$$

To recover these parameters, I use simulated methods of moments and bootstrap my data to estimate standard errors. From the data, I choose the following moments of informed-traded earnings announcements: average realized returns ($\bar{R}_t$), average liquidity ($\bar{L}_t$), and average returns interacted with liquidity ($\overline{RL}_t$). Define this empirical moment vector for the informed traded earnings announcements as

$$m_t^{emp} = (\bar{R}_t, \bar{L}_t, \overline{RL}_t) \tag{12}$$

Table 5 reports these moments by quarter estimated from the sample.

Define the simulated moments m^{sim} which are a function of the parameters $\theta = (\beta_2, \beta_3, \sigma_\epsilon^2)$ to be

$$m_t^{sim} = \left(\bar{R}_t(\theta), \bar{L}_t(\theta), \overline{RL}_t(\theta)\right) \tag{13}$$

To estimate these simulated moments, I perform 1,000 simulations of signal noise (ϵ_i) for each of the N_t earnings announcements using noise parameter σ_ϵ^2. For each simulation, I identify the earnings announcements that the informed traders would choose conditional on parameters

(β_2, β_3) and data (R_i, L_i). I estimate the simulated moments as an average across each simulation.

To match these moments, I minimize the difference $G_t = m_t^{emp} - m_t^{sim}$ and estimate parameters

$$\hat{\theta} = argmin_\theta\big(G_t(\theta)' W_t G_t(\theta)\big) \tag{14}$$

using the identity matrix as a standard positive definite weighting matrix. Duffie and Singleton (1993) prove that under standard regularity conditions, the simulated method of moments is asymptotically consistent. To estimate standard errors, I bootstrap with replacement the earnings announcement data on returns and liquidity. Table 5 reports parameter estimates and model fit. The model manages to accurately fit the simulated moments $\bar{R}_t$, $\bar{L}_t$, and $\overline{RL}_t$ with root-mean-square errors (RMSE) of 0.07, 0.42, and 1.15 *seriatim*.

Consistent with reduced form estimates, the informed traders preferred earnings announcements with greater liquidity, higher returns, and larger liquidity times returns. The parameter estimates imply that the informed traders were on average willing to forgo one percent of expected return in exchange for 0.65 standard deviations of liquidity. This tradeoff is consistent in direction with the predictions of informed trade theory. Liquidity and expected return jointly determine the profitability of informed trade. The estimated coefficient on the interaction term between liquidity and returns is also positive and statistically significant. This positive interaction term implies that informed traders especially preferred earnings announcements with high expected returns and liquidity.

On average across quarters, the noisiness of earnings signals is 15.7%, which implies a signal-to-noise ratio (σ_R/σ_ϵ) of 0.4. The standard deviation to earnings returns is only 40% as large as that of signal noise. This SNR varies from a low of 20% in 2012 Q2 to a high of 60% in 2014 Q4. The performance of the informed traders varied substantially across quarters (Table 5, column (1)). This variation in performance implies that earnings announcements differ significantly in informativeness about stock price responses from quarter to quarter. The magnitude of this SNR is comparable to that of a reasonable trading strategy.

For comparison, I construct a benchmark trading strategy using only the earnings per share information of the earnings announcement. For each earnings announcement, I estimate a historical earnings response coefficient. The earnings response coefficient is empirically estimated as

$$R_t = \alpha + ERC_i^{EPS}\left(\frac{EPS_t - \overline{EPS}_{i,t}}{P_{t-1}}\right) + \epsilon_t \tag{15}$$

where ERC_i^{EPS} is the earnings response coefficient, EPS_t is earnings per share, $\overline{EPS}_{i,t}$ is the market expectation of firm earnings, and P_{t-1} is the one month-lagged stock price. For the market expectation of firm earnings, I use consensus analyst forecasts as a proxy. For each firm-earnings announcement observation, I estimate ERC_i^{EPS} using the past three years of earnings announcements. This yields a time-varying, rolling window estimate of $ERC_{i,t-1}^{EPS}$ for each quarter, which uses only historical data. The model predicts earnings announcement returns:

$$\widehat{R_t} = ERC_{i,t-1}^{EPS}\left(\frac{EPS_t - \overline{EPS}_{i,t}}{P_{t-1}}\right) \tag{16}$$

For each quarter, the trading strategy chooses the earnings announcement with the largest predicted return among the earnings announcements above the 25th percentile of liquidity. On average, this trading strategy performs better than that of the informed traders. Figure 2 Panel A plots the Epanechnikov kernel density of the benchmark trading strategy earnings announcement returns relative to that of non-traded earnings announcements. Panel B directly compares this performance with that of Figure 1 Panel A. The red-dashed line is the difference between the densities in Figure 2 Panel A (model performance) and the black-dashed line is the difference between the densities in Figure 1 Panel A (informed trader performance). This benchmark trading strategy identifies earnings announcements with an average absolute return of 5.51% which is statistically significantly larger than the 4.98% of the informed traders at the 1%

confidence level. However, when controlling for liquidity in the model, the average implied SNR ratio is 0.42, which is similar to the 0.4 SNR implied by the performance of the informed traders. The following section empirically explores potential sources of noise to the signal quality of earnings announcements.

5. Empirical Analysis of Potential Sources of Noise

The empirical findings thus far document that sophisticated investors perform poorly when predicting stock price responses to earnings announcements. The trading strategy is consistent with insider trading theory. The investors on average traded earnings announcements with greater realized returns and more liquidity. However, about 70% of their trades were of earnings outside the bottom and top deciles of returns. Despite having the earnings announcement in advance, the informed traders had difficulty identifying earnings with the largest stock price responses.

In this section, I discuss two potential sources of noise and test whether they contribute to low earnings informativeness. The identifying assumption is that there exists variation in the signal-to-noise ratio by earnings announcement, which is *ex-ante* observable by the informed traders. The empirical strategy is to construct proxies for the uncertainty of earnings announcement signals of stock price responses. I construct proxies of *ex-ante* and *ex-post* uncertainty. Kim and Verrecchia (1991, 1994, 1997) formalizes this uncertainty in a model of stock price response to earnings announcement. *Ex-ante* uncertainty is due to pre-announcement private information. Through trade, the market incorporates private signals about earnings announcement expectations. *Ex-ante* uncertainty is the noisiness by which the informed traders may infer the market expectation of earnings. *Ex-post* uncertainty is due to event-period private information. Investors heterogeneously interpret the earnings announcement disclosures, resulting in large earnings announcement trading volumes. *Ex-post* uncertainty is the ambiguity of the marginal investors' interpretation of the earnings announcement.

5.1 *Ex-Ante* Uncertainty

The value of having the earnings announcements in advance depends on the ability of the informed traders to infer market expectations. This inference is greatly simplified by analyst forecasts of earnings announcements. These forecasts are public signals of market expectations of earnings. However, these forecasts are not always in perfect agreement. I measure the level of noise in market expectations of earnings through analyst forecast dispersion. Analyst forecast $EPS_{i,t}$ disagreement ($D_{i,t}^{EPS}$) is defined as the standard deviation to $EPS_{i,t}$ analyst forecasts scaled by historical price:

$$\left(D_{i,t}^{EPS}\right)^2 = \frac{1}{N_{i,t}} \sum_j \frac{\left(EPS_{i,t} - \overline{EPS}_{i,t}\ \right)^2}{P_{i,t-1}} \tag{17}$$

where $N_{i,t}$ is the number of analysts for stock i and earnings announcement time and $\overline{EPS}_{i,t}$ is the average analyst $EPS_{i,t}$ forecast. I scale earnings per share variance by price to standardize firms along a price-earnings ratio dimension. Similarly, for revenue forecast disagreement:

$$\left(D_{i,t}^{Rev}\right)^2 = \frac{1}{N_{i,t}} \sum_j \frac{\left(Rev_{i,t} - \overline{Rev}_{i,t}\ \right)^2}{\overline{Rev}_{i,t}} \tag{18}$$

I scale revenue dispersion by current average revenue forecast for size standardization.

The hypothesis is that informed traders avoid earnings announcements with high average analyst forecast disagreement for earnings and revenue. The economic intuition is that when analyst forecasts are more dispersed, the informed traders are less certain as to what expectations the market has priced. To empirically test this hypothesis, I measure the extent to which informed traders avoid earnings announcements where analysts disagree. As an empirical proxy, I use the average disagreement of revenue and earnings forecasts disagreement $\left(D_{i,t}\right)$.

An alternative more reduced-form measure of the noise in market expectations relies on information spillover effects. When a firm announces earnings information, the market updates its expectation about similar firms. This updating process happens quickly during the earnings season. Analyst forecasts may become stale relative to market prices. These information spillovers increase the difficulty of inferring what the market has already priced. Thus, I hypothesize that informed traders avoid earnings announcements that immediately follow a similar firm. I define similar firm by 4-digit SIC industries. I construct a dummy variable ($Near_{i,t}$) equal to 1 if in the past two weeks an above median-sized firm within the same industry released earnings, and zero otherwise. I condition on a large firm (above median-size) such that the firm is representative of the industry and informative about other industry firms. I empirically test this hypothesis by measuring the covariance of informed trade and the proximity of a similar earnings announcement.

5.2 *Ex-Post* Uncertainty

Ambiguity about the marginal investor's interpretation of earnings information depends on the scope of disagreement. I hypothesize that informed investors avoid earnings announcements where the information may be heterogeneously interpreted. I empirically proxy for the degree of interpretation heterogeneity with signal disagreement and guidance. Controlling for the magnitude of earnings and revenue surprise, the scope of disagreement depends on the signal dispersion. If earnings and revenue surprise are both in the same direction, then there is less scope for differential interpretation. However, if a firm beats earnings expectations, but misses revenue expectations, then the stock price return depends more on the relative weight of earnings vs. revenue. The first proxy of *ex-post* uncertainty is signal agreement $\left(s_{i,t}^{agree}\right)$: whether or not earnings and revenue surprise are in the same direction.

The second proxy of information heterogeneity is the availability of managerial guidance. Controlling for whether guidance beat or missed analyst expectations, the existence of guidance decreases the ambiguity of soft, qualitative information within earnings announcements. I define an indicator variable $G_{i,t}$ equal to 1 if there is guidance and zero otherwise. Without explicit managerial guidance, the market's interpretation of forward-looking earnings statements is more ambiguous.

5.3 Controls of Earnings Announcement Information Content

In testing potential sources of noise, I need to control for the earnings announcement signal and asset liquidity. I use a standard measure of liquidity (see Section 3.3) and construct measures of earnings and managerial guidance surprise. In controlling for the earnings signal, I am reducing the dimensionality of earnings announcement information. I do so by focusing on three components of earnings announcements: earnings per share, revenue, and managerial forecasts. These three components summarise the information contained in an earnings announcement. The information content of these is relative to market expectations. I estimate surprise for each signal as the difference between the reported and market-expected signal. Setting noise in the market expectation aside, I measure the market-expected signal as the average of analyst forecasts. I adjust both earnings per share surprise and revenue surprise by historical earnings response coefficients (see equation (15)). Adjusting for the earnings response coefficient is designed to capture firm-specific differences in the relevance and accuracy of these measures for firm fundamental value.

$$S_{i,t}^{EPS} = ERC_{i,t-1}^{EPS}\left(\frac{EPS_{i,t} - \overline{EPS}_{i,t}}{P_{i,t-1}}\right) \tag{19}$$

$$\mathrm{S}_{\mathrm{i,t}}^{\mathrm{Rev}} = \mathrm{ERC}_{\mathrm{i,t-1}}^{\mathrm{Rev}}\left(\frac{\mathrm{Rev}_{\mathrm{i,t}} - \overline{Rev}_{i,t}}{P_{i,t-1}}\right) \tag{20}$$

Managerial guidance is less comparable to that of earnings per share and revenue signals. I discretize the guidance estimate to confirm, miss, and beat. Guidance within 10% of analyst expectations confirms the outlook of the firm. Guidance below 10% of analyst expectations qualifies as a miss and guidance above 10% qualifies as a beat. Managerial guidance strengthens the earnings signal if the guidance surprise is in the same direction as earnings and revenue surprise. I define an indicator variable $GS_{i,t}$ that is equal to 1 if the surprise is in the same direction as both earnings and revenue surprise and 0 otherwise.

The signals are representative if they effectively capture the information in earnings announcements (I_{t+1}) used by investors. The hypothesis is that informed traders use these signals to form expectations about earnings announcement returns. I test this hypothesis by measuring the extent to which the signals covary with informed trade.

5.4 Empirical Results: Earnings Signals and Noisy Estimates

To test the two potential sources of noise, I use a Logit model of informed trade. The model specification follows equation (5), but with a larger set of explanatory variables. The precise regression formula is described in Table 7 equation (24). As measures of *ex-ante* uncertainty, I use average analyst disagreement and proximity to a similar firm's earnings announcement. As measures of *ex-post* uncertainty, I use earnings per share and revenue surprise signal agreement and the existence of managerial guidance. To control for the information content of earnings announcements, I use average earnings and revenue surprise and an indicator variable for whether guidance surprise was in the same direction of earnings and revenue surprise.

Table 7 presents the results. For ease of interpretation, I standardize all continuous explanatory variables such that one unit is a standard deviation and report the marginal effects. The marginal effects are estimated at the means of liquidity, average earnings and revenue surprise, and analyst disagreement. Standard errors are clustered by quarter. In the baseline specification, column (1) does not include any fixed effects. Column (2) includes quarter fixed effects and column (3) includes quarter and industry fixed effects. In the following discussion, I analyze the baseline estimates. However, the findings are qualitatively robust to quarter and industry fixed effects.

Informed traders avoid earnings announcements with *ex-ante* uncertainty: ambiguity about what the market has already priced. A one standard deviation in analyst forecast disagreement is associated with a 22% decrease in probability of informed trade. Furthermore, if a comparable firm recently released an earnings announcement, informed trade is 19% less likely.

Informed traders prefer earnings announcements that are less likely to be subject to uncertain market interpretation. Conditional on the level of earnings and revenue surprise, if the two signals agree, then informed trade is 40% more likely. Furthermore, if managers make explicit their soft guidance with a guidance estimate, then informed trade is 25% more likely. The trading strategy strongly covaries with indicators of low potential for heterogenous interpretation

6. Additional Analyses and Robustness

6.1 Detection risk

An important constraint to profit maximization is detection risk. Since the informed trading was illegal, the cost of detection was high: the seizure of illegal profits and likely imprisonment. The component of detection risk related to price impact and liquidity are observable and controlled for in the empirical estimation. However, there may be other, unobservable components of detection risk. For example, the informed traders may know that the general counsel of firm A better investigates cases of insider trading than that of firm B. General counsels mitigate the informed trading of corporate insiders and their efficacy varies across firms (Jagolinzer et al., 2011). Insofar as the cross-sectional variation in detection risk is uncorrelated with earnings announcement returns and liquidity, the performance estimates are unbiased. Firm-specific detection risk is unlikely to be related to earnings returns. However, liquidity is likely to be positively correlated with corporate governance (and negatively correlated with detection risk). Less informed trading decreases information asymmetry in markets, which increases liquidity. The estimated covariance between the propensity to informed trade and liquidity may be negatively biased due to detection risk.

In addition to impacting the choice of earnings announcement to informed trade on, detection risk may incentivize informed traders to manage profits. Informed traders may avoid the most profitable earnings announcements due to detection risk. However, their trading behavior for salient, unscheduled disclosures is inconsistent with this hypothesis. Examples of such disclosures include patent rulings, clinical trial outcomes, and litigation results. Frequently, there is a narrow window of two to three hours between newswire server upload (informed trader access) and dissemination (public access). If the informed traders sought to earn modest profits, they would have avoided these salient events. An alternative means of managing profits is to avoid large profits within a given period. For example, after making exceptionally large profits yesterday, the informed traders may intentionally make smaller gains today. I empirically test whether the trading strategy exhibits time-series patterns of managing profits. If informed traders were attempting to avoid exceeding a threshold of profits or average return, I expect to find negative autocorrelation in performance.

Table 8 documents that performance is mildly positively autocorrelated at the daily and weekly frequencies for both dollar profits and returns. I further test this hypothesis by assessing the extent to which performance leading up to week-end or month-end can predict performance of trades at period-end. When the informed traders make large profits leading up to the end of a week or month, they do not tend to perform worse (Table 9). In short, the informed traders are not window-dressing performance near the end of weeks or months to avoid detection. I fail to find any evidence of time-series patterns to informed trade associated with avoiding detection risk at the expense of profit maximization.

These findings do not rule out detection risk but rather show that detection risk is not a threat to identification. The informed traders may have managed detection risk by restricting the quantity of shares traded. On average, the informed trader's dollar volume prior to the earnings announcement was 3.85% of total dollar volume. Additionally, they may have restricted the number of traded earnings announcements. On average, they traded 9.25% of earnings announcements.

6.2 Endogeneity of Earnings Announcement Returns

So far, I have treated earnings announcement returns as exogenous to the trading of informed investors. However, insofar as prices respond to quantities, the earnings announcement return may be endogenous. This endogeneity is carefully modeled in Brunnermeier (2005), where he distinguishes between long-run and short-run private information. In this setting, the informed traders have short-run private information: access to the earnings announcement two to three hours in advance. Prior to the earnings announcement, the quantity traded by the informed trader has price impact. However, the market does not know whether this information is short-run or long-run. If the market incorrectly infers that this information is in part long-run, then the market may double count the earnings announcement information. This double counting is the source of the endogeneity.

To illustrate this endogeneity, consider this simple model of earnings announcements. Let P_t be the stock price before the earnings announcement and P_{t+1} be the price after. Define I_t to be a vector of information about the firm's fundamental value priced by market at time t. The earnings announcement is a public signal about firm fundamentals and denoted I_{t+1}. Define β_t to be the information response coefficient, which is the change in prices associated with a change in information. By definition, the stock price response to an earnings announcement is

$$P_{t+1} - P_t = \beta_t(I_{t+1} - I_t) \tag{21}$$

Figure 3 provides an example of when an earnings announcement with positive news is released at market close (after 4:00 PM ET). The informed traders receive this earnings announcement in advance of the market at 1:00 PM ET. Without informed trade, the new price after the earnings announcement would be $p^T_{9:30am}$. This price is $\beta_t(I_{t+1} - I_t)$ larger than the pre-announcement price prior to informed trade (p_{1pm}). Without informed trade, the earnings announcement return is

$$p^T_{t+1,9:30am} - p_{t,1pm} = \beta_t \Delta I_{t+1} \tag{22}$$

With informed trade, the pre-announcement price increases from p_{1pm} to p_{4pm} due to the price impact of the informed trade. If the market fully attributes this informed trade to long-run private information, unrelated to the earnings announcement, then the post earnings announcement price is $P^O_{t,9:30am}$. With informed trade the earnings announcement return is

$$p^O_{t+1,9:30am} - p_{t,1pm} = \beta_t \Delta I_{t+1} + \left(p_{\mathrm{t},4pm} - p_{t,1pm}\right) \tag{23}$$

The pre-announcement informed trade endogenously increases the earnings announcement return. This is the source of endogeneity between informed trade and earnings announcement returns. The 1:00 PM to 4:00 PM ET price change $\left(p_{\mathrm{t},4pm} - p_{t,1pm}\right)$ is the upper bound to the endogeneity effect. If the market fully attributes the pre-announcement informed trade to short-run private information, then informed trade price impact is perfectly netted against $\beta_t \Delta I_{t+1}$. In this case, there is no endogeneity.

In the previous section, I estimated the upper bound to the covariance between the informed trading strategy and earnings announcement returns. This upper bound is the true covariance if the market fully attributed the informed trade prior to announcement to short-term private information. Here, I estimate the lower bound by assuming the opposite: the market fully attributed the informed trade to long-term private information. To do so, I adjust the earnings announcement return to fully exclude the period for which the informed traders had price impact. In the above example, I estimate the earnings announcement return as the log difference between 9:30 AM and the previous day 4:00 PM ET. This entirely excludes the price impact of informed traders.

I re-estimate the Logit model, in equation (5), of informed trade using the earnings announcement return for the narrower window which excludes the price impact of the informed traders. Table 10 presents the results in an analogous manner to Table 3. As expected, the estimated coefficient on narrow earnings announcement returns is smaller. Relative to the mean probability of informed trade, a one standard deviation increase in returns is associated with a 15% increased probability of informed trade. This baseline effect (column (1)) is smaller, but not statistically significantly different, than the 19% effect found when including the price impact of informed traders.

Similarly, I re-estimate the price impact model in equation (6) using the earnings announcement return for the narrower window. Table 11 presents the results in a manner analogous to Table 4. For each additional percentage point of narrow earnings announcement returns, the informed traders generated 4.6 bps more price impact. This baseline lower-bound estimate is statistically significantly different from the upper-bound estimate of 8.5 bps.

Endogeneity of earnings announcement returns and informed trade positively biases the performance metrics. These lower-bound estimates confirm that the trading strategy does covary with return, liquidity and time to trade. The results are not driven by endogenous bias. However, the lower-bound estimates show a worse performance of informed traders. Along both the extensive and intensive margin, the covariance is weaker between informed trade and future earnings announcement return.

6.3 Robustness to Liquidity Controls

For the informed traders' constrained profit maximization, liquidity is of first order importance. Therefore, this section considers alternative proxies and functional forms of liquidity. When estimating the covariance between realized returns and informed trade, the regression specification (5) includes a continuous control variable for liquidity (log 1-month average dollar volume prior to the earnings announcement). Instead of a continuous control, I split the sample by five quintiles of liquidity and re-estimate the regression specification (31). Table 12 Panel A presents the regression results and the fraction of informed trade in each quintile. For the least liquid quintile (1), 1.92% of earnings announcements are traded by the informed traders. For the most liquid quintile (5), 14.63% of earnings announcements are traded on by the informed traders. Informed trade is increasing by liquidity quintile. The covariance between realized return and informed trade is positive and significant for each subsample of the data. Within each quintile of liquidity, earnings announcements with higher realized returns are more likely to be informed traded. Similar to Table 3 Panel A, coefficients report at-means marginal effects of a one standard deviation increase in realized returns on the probability of informed trade. The magnitudes of estimates are economically similar and slightly larger for high liquidity quintiles. On average, a one standard deviation increase to realized returns is associated with a 1.93 percentage point increase in the probability of informed trade, which is a 20% increase relative to the unconditional mean of 9.25%.

As an alternative measure of liquidity, I use the 1-month average, dollar-weighted bid-ask spread prior to the earnings announcement, from WRDS Intraday Indicators. Table 12 Panel B presents the regression results and fraction of informed trade in each quintile of this alternative measure of liquidity. The findings are robust to this alternative definition of liquidity: informed trade is increasing in liquidity and within each quintile of liquidity informed traded earnings announcements tend to have larger realized returns.

7. Conclusion

Using a unique empirical setting where sophisticated investors informed traded earnings announcements, I document that financial disclosures are noisy signals of stock price responses. Consistent with theory, the informed traders targeted earnings announcements with more surprising news and liquid equities. Despite this informational advantage, the informed traders performed poorly. Controlling for liquidity, 31% of the informed trades were within the bottom and top deciles of earnings announcement returns. Using my model of informed trade, I estimate that the signal-to-noise ratio of earnings announcements is 0.4. This estimate is causal: signal quality determined the informed traders' performance. For comparison, a benchmark trading strategy based on earnings surprise attains 37% of trades in the bottom and top deciles of earnings returns. The benchmark implies a similar SNR estimate of 0.42. This low signal quality implies that individuals cannot infer stock market responses from the information in earnings announcements. Building on extant theory, I explore two potential sources of noise in the information environment of earnings announcements: (i) *ex-ante* ambiguity about the market's expectation of earnings and (ii) *ex-post* uncertainty about the market's interpretation of the disclosure. Using proxies for both types of noise, I document that the informed traders avoided noisier earnings announcements. These findings highlight the shortcoming of earnings announcements in informing individual investors.

Appendix A: Legend of Variables

Variable Name	Description	Source
Informed Trade	An indicator variable equal to 1 if the earnings announcement is informed traded and 0 otherwise. See Section 3.2 for details on the sample construction of the informed-traded observations.	PACER, FOIA, Marketwire, Factiva
$R_{i,t}$	$R_{i,t}$ is the earnings announcement return for firm i and time t. The return window may vary depending on certainty of the holding period. See Section 3.3 for details on the return window construction.	CRSIP, Wall Street Horizons
$\underline{R_{i,t}}$	$\underline{R_{i,t}}$ is the endogeneity corrected earnings announcement return (earnings return excluding the 1-4pm window prior to announcement).	CRSIP, Wall Street Horizons
$\rho_{i,t}$	$\rho_{i,t}$ it the estimate of the informed traders' price impact for firm i and time t. Price impact is estimated to be the stock price return between 1pm and 4pm prior to the earnings announcement for the informed traded earnings announcements.	CRSIP, Wall Street Horizons
Industry FE	Industry variables for each of the Fama-French 10 factor portfolios.	Fama-French
Time FE	Indicator variables for each quarter of the sample.	Wall Street Horizons
Analyst Following	The number of analysts that made a forecast for the firm's earnings.	IBES
Control Volume	The average dollar trading volume for 20 trading days (1-month) leading up to 5-days before the earnings announcement.	CRSP
$L_{i,t}$	The logarithm of control volume.	CRSP
Abnormal Volume	The average trading volume for the 3-days after the earnings announcement divided by control volume.	CRSP
$G_{i,t}$	$G_{i,t}$ is an indicator variable equal to 1 if management issued guidance concurrently with the earnings announcement and 0 otherwise.	IBES
Max_TT	Maximum time to trade (Max_TT) is the difference between the distribution time of the earnings announcement (when it became public) and the upload time (when the informed traders had access).	FOIA
TT	Time to trade (TT) is the difference between the first informed trade and when the earnings announcement became public.	FOIA

Holding	The difference between the time of the first informed trade prior to the earnings announcement and when the informed traders closed the position. The data on $PL_{i,t}$ and $TD_{i,t}$ are aggregated for all trades affiliated with an earnings announcement. For summary statistics, I exclude any aggregated data for which the maximum holding period is greater than 5-days.	FOIA
$T_{i,t}$	An indicator variable equal to 1 if the earnings announcement is publicly released between 4 and 5 pm.	Wall Street Horizons
$PL_{i,t}$	The profit and loss of informed traders made in association with the earnings announcement of firm i and time t. I require the holding window for the FOIA data to be less than 5-days.	FOIA
$TD_{i,t}$	The total dollars invested by the informed traders in association with the earnings announcement of firm i and time t. I require the holding window for the FOIA data to be less than 5-days.	FOIA
$\overline{PL}_{t,-}$	The total profit and loss for period t across multiple earnings announcements, excluding the final 3 earnings announcement trades within the period.	FOIA
$RI_{i,t}$	$RI_{i,t}$ is the return of informed traders for firm i and time t. $RI_{i,t}$ is $PL_{i,t}$ divided by total dollars traded.	FOIA
$\bar{R}_{t,-}$	The return of informed traders aggregated over period t, excluding the final 3 earnings announcement trades within the period.	FOIA
$EPS_{i,t}$	The earnings announcement reported earnings per share for firm i and time t.	Compustat, IBES
$\overline{EPS}_{i,t}$	The consensus analyst expectation of earnings per share for firm i and time t.	IBES
$Rev_{i,t}$	The revenue reported earnings per share for firm i and time t.	Compustat, IBES
$\overline{Rev}_{i,t}$	The consensus analyst expectation of revenue for firm i and time t.	IBES
$D_{i,t}^{EPS}$	$\left(D_{i,t}^{EPS}\right)^2 = \frac{1}{N_{i,t}^{EPS}}\sum_j \frac{\left(EPS_{j,i,t} - \overline{EPS}_{i,t}\right)^2}{P_{i,t-1}}$ $EPS_{j,i,t}$ is the forecast made by analyst j for the earnings announcement of firm i made at time t. $N_{i,t}^{EPS}$ is the number	IBES, CRSP

	of analysts that made an EPS forecast for the earnings announcement. $P_{i,t-1}$ is share price lagged by 1-month.	
$D_{i,t}^{Rev}$	$$\left(D_{i,t}^{Rev}\right)^2 = \frac{1}{N_{i,t}^{REV}} \sum_j \frac{\left(Rev_{i,t} - \overline{Rev}_{i,t}\right)^2}{\overline{Rev}_{i,t}}$$ $Rev_{j,i,t}$ is the forecast made by analyst j for the earnings announcement of firm i made at time t. $N_{i,t}^{Rev}$ is the number of analysts that made an EPS forecast for the earnings announcement.	IBES, CRSP
$D_{i,t}$	The average of $D_{i,t}^{EPS}$ and $D_{i,t}^{Rev}$.	IBES, CRSP
$Near_{i,t}$	$Near_{i,t}$ is an indicator variable equal to 1 if an above median sized firm within the same industry group (4-digit SIC code) reported earnings within 14 days of the firm's earnings announcement.	Wall Street Horizons, Compustat
$s_{i,t}^{agree}$	$s_{i,t}^{agree}$ is an indicator variable equal to 1 if earnings surprise and revenue surprise are in the same direction.	IBES
$GS_{i,t}$	An indicator variable equal to 1 if guidance surprise is in the same direction as earnings and revenue surprise.	IBES
$S_{i,t}^{EPS}$	$$S_{i,t}^{EPS} = ERC_{i,t-1}^{EPS}\left(\frac{EPS_{i,t} - \overline{EPS}_{i,t}}{P_{i,t-1}}\right)$$	IBES, CRSP
$S_{i,t}^{Rev}$	$$\mathrm{S_{i,t}^{Rev}} = \mathrm{ERC_{i,t-1}^{Rev}}\left(\frac{\mathrm{Rev_{i,t}} - \overline{Rev}_{i,t}}{P_{i,t-1}}\right)$$	IBES, CRSP
$S_{i,t}$	$S_{i,t}$ is the absolute value of the average of $S_{i,t}^{EPS}$ and $S_{i,t}^{Rev}$: $$S_{i,t} = \mid S_{i,t}^{EPS} + S_{i,t}^{Rev} \mid$$	IBES, CRSP

Appendix B: Detailed Discussion of Institutional Setting

Commercial news wire companies – sometimes referred to as wire services, or news agencies – are an important information intermediary. Newswires collect news reports and disseminate this information to subscribing news organizations or media companies including newspapers, television/radio broadcasters, freelance journalists, etc. These news organizations then further publicize the news to their respective audiences – businesses, households, and individuals. Firms use newswire companies to fairly disseminate press releases. Examples of firm press releases range from earnings announcements and lawsuit results to product launches and events coverage. A commercial newswire would receive a preliminary press release from a company, edit and format the release, and store it in embargo until a pre-designated release time.

The empirical setting in this paper involves three commercial newswire companies. PR Newswire (acquired by Cision in 2016), Marketwired (acquired by NASDAQ in 2016, and subsequently sold to West Corporation in 2018), and Business Wire (a subsidiary of Berkshire Hathaway since 2006) are industry leaders of commercial newswires. Anecdotally, their pricing structure depends on distribution (e.g. regional/national, special demographics/interests, web-only, etc.), text length, and use of multimedia. The price of a single press release could range from a few hundred to a few thousand dollars. According to G2 Crowd, a third-party firm specializing in reviewing and comparing business solutions, these three newswires are the most popular and go-to distributors of firm news. Former Senior Vice President and General Counsel at Panera Bread, Louis DiPietro, explained during witness testimony, that sending earnings announcements and guidance to a newswire for public dissemination is the best way for firms to comply with Regulation Fair Disclosure.

From early 2011 to 2015, an international ring of hackers breached the servers of PR Newswire, Marketwired, and Business Wire. These hackers used a variety of methods to "backdoor" into the newswires' servers to access confidential press releases prior to their publication. These hackers rotated use of SQL injections, stolen identifications, Trojan malware, and web shells to gain unlimited access to over 150,000 unique press releases. These press releases included patent results, clinical trial updates, acquisition announcements, earnings announcements, and so on.

The hackers, who are mainly based out of Russia and Ukraine, illicitly sold newswire server access to an international group of financial professionals. The hackers negotiated an equity payment with the traders. Up to 50% of the profits generated from trading on the stolen information would be paid to the hacker group via a middleman in exchange for continued access to the newswire servers.

In August 2015, investigations by the United States Secret Service (USSS) and the Federal Bureau of Investigations (FBI) led to the first arrest of some of the traders involved. In the same week, the Securities and Exchange Commission (SEC) filed fraud charges against 32 defendants who were part of the insider trading cartel. An official inquiry into this illegal hacking and insider trading case was opened and led by the Department of Justice (DOJ), several district U.S. Attorney's Offices (USAO), The USSS, the FBI, the Department of Homeland Security (DHS), and the SEC.

Importantly, what initially raised suspicion and eventually led to a case being opened was not the trading patterns or investment behaviour of the traders. The inception of the investigation was neither credited to FINRA nor the SEC. From 2012, the three targeted newswires began frequently noticing the presence of malware on their servers and other holes in their cybersecurity. Several cybersecurity firms were involved. The FBI launched a criminal investigation in tandem with the USSS that eventually led them to the discovery of this hacker ring. For various reasons, including political motivation and corruption of Ukrainian officials, the case went cold, and the hackers continued their illegal activity. The cartel of traders continued to enjoy intermittent access to these press releases. When one of the hackers was arrested on U.S. soil in December 2014, none of the traders was informed. The traders spoke exclusively to the middleman and were not aware of the identity of the hackers.

But just as the newswires did not always inform their clients that they were having security problems, the middlemen appear to have chosen not to tell the traders that one of their hackers was arrested.

---- Isobel Koshiw, The Verge

A potential explanation for why the traders were not caught is provided by Maggio et. al (2019). Frequently, insider trading is discovered due to complaints by the losing counterparty. However, Maggio et. al (2019) document that financial intermediaries profit by selling informed order flow information to their best clients. Insofar as the illegally informed insiders sufficiently limit the size of their trades, their immediate counterparties may profit by reselling the information. The dispersion of the information rents decreases the incentive of each counterparty to report the suspicious trading.

Official investigations are still ongoing at the time of this paper. At least thirty different individuals and entities have reached settlements with the SEC. At least two individuals have been found guilty and sentenced. Former SEC Chair Mary Jo White stated in an official press release:

This international scheme is unprecedented in terms of the scope of the hacking, the number of traders, the number of securities traded and profits generated… These hackers and traders are charged with reaping more than $100 million in illicit profits by stealing nonpublic information and trading based on that information. That deception ends today as we have exposed their fraudulent scheme and frozen their assets.”

References

Abarbanell, Jeffery S., William N. Lanen, and Robert E. Verrecchia. "Analysts' forecasts as proxies for investor beliefs in empirical research." *Journal of Accounting and Economics* 20.1 (1995): 31-60.

Admati, Anat R., and Paul Pfleiderer. "A theory of intraday patterns: Volume and price variability." *The Review of Financial Studies* 1.1 (1988): 3-40.

Ahern, Kenneth R. "Information networks: Evidence from illegal insider trading tips." *Journal of Financial Economics* 125.1 (2017): 26-47.

Akey, Pat, Vincent Gregoire, and Charles Martineau. "Retail Insider Trading and Market Price Efficiency: Evidence from Hacked Earnings News." *Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3365024*

Ball, Ray, and Philip Brown. "An empirical evaluation of accounting income numbers." *Journal of Accounting Research* (1968): 159-178.

Ball, Ray, and Stephen P. Kothari. "Security returns around earnings announcements." *Accounting Review* (1991): 718-738.

Ball, Ray, and Lakshmanan Shivakumar. "Earnings quality at initial public offerings." *Journal of Accounting and Economics* 45.2-3 (2008): 324-349.

Beaver, William H., Maureen F. McNichols, and Zach Z. Wang. "The information content of earnings announcements: new insights from intertemporal and cross-sectional behavior." *Review of Accounting Studies* 23.1 (2018): 95-135.

Beaver, William H., Maureen F. McNichols, and Zach Z. Wang. "Increased market response to earnings announcements in the 21st century: An Empirical Investigation." *Journal of Accounting and Economics* (2019): 101244.

Beyer, Anne, et al. "The financial reporting environment: Review of the recent literature." *Journal of Accounting and Economics* 50.2-3 (2010): 296-343.

Brunnermeier, Markus K. "Information leakage and market efficiency." *The Review of Financial Studies* 18.2 (2005): 417-457.

Campbell, John Y., et al. "The econometrics of financial markets." *Princeton University press*, 1997.

Collins, Daniel W., Oliver Zhen Li, and Hong Xie. "What drives the increased informativeness of earnings announcements over time?" *Review of Accounting Studies* 14.1 (2009): 1-30.

Cornell, Bradford, and Erik R. Sirri. "The reaction of investors and stock prices to insider trading." *The Journal of Finance* 47.3 (1992): 1031-1059.

Davis, Angela K., Jeremy M. Piger, and Lisa M. Sedor. "Beyond the numbers: Measuring the information content of earnings press release language." *Contemporary Accounting Research* 29.3 (2012): 845-868.

DeHaan, Ed, Terry Shevlin, and Jacob Thornock. "Market (in) attention and the strategic scheduling and timing of earnings announcements." *Journal of Accounting and Economics* 60.1 (2015): 36-55.

Diamond, Douglas W., and Robert E. Verrecchia. "Constraints on short-selling and asset price adjustment to private information." *Journal of Financial Economics* 18.2 (1987): 277-311.

Di Maggio, Marco, Francesco Franzoni, Amir Kermani, and Carlo Sommavilla. "The relevance of broker networks for information diffusion in the stock market." *Journal of Financial Economics* (2019).

Duffie, D., and K. J. Singleton. "Simulated moments estimation of Markov models of asset prices., *Econometrica* 61 929–95 (1993).

Dow, James, and Gary Gorton. "Profitable informed trading in a simple general equilibrium model of asset pricing." *Journal of Economic Theory* 67.2 (1995): 327-369.

Easley, David, and Maureen O'hara. "Price, trade size, and information in ecurities markets." *Journal of Financial Economics* 19.1 (1987): 69-90.

Fama, Eugene F., and Kenneth R. French. "Industry costs of equity." *Journal of Financial Economics* 43.2 (1997): 153-193.

Francis, Jennifer, Katherine Schipper, and Linda Vincent. "Earnings announcements and competing information." *Journal of Accounting and Economics* 33.3 (2002): 313-342.

Glosten, Lawrence R., and Paul R. Milgrom. "Bid, ask and transaction prices in a specialist market with heterogeneously informed traders." *Journal of Financial Economics* 14.1 (1985): 71-100.

Grossman, Sanford J., and Joseph E. Stiglitz. "On the impossibility of informationally efficient markets." *The American Economic Review* 70.3 (1980): 393-408.

Grundy, Bruce D., and Maureen McNichols. "Trade and the revelation of information through prices and direct disclosure." *The Review of Financial Studies* 2.4 (1989): 495-526.

Harris, Milton, and Artur Raviv. "Differences of opinion make a horse race." *The Review of Financial Studies* 6.3 (1993): 473-506.

Henry, Elaine. "Are investors influenced by how earnings press releases are written?." *The Journal of Business Communication (1973)* 45.4 (2008): 363-407.

Holthausen, Robert W., and Robert E. Verrecchia. "The effect of informedness and consensus on price and volume behavior." *Accounting Review* (1990): 191-208.

Indjejikian, Raffi J. "The impact of costly information interpretation on firm disclosure decisions." *Journal of Accounting Research* 29.2 (1991): 277-301.

Jagolinzer, Alan D., David F. Larcker, and Daniel J. Taylor. "Corporate governance and the information content of insider trades." *Journal of Accounting Research* 49.5 (2011): 1249-1274.

Kacperczyk, Marcin, and Emiliano S. Pagnotto "Chasing Private Information*" The Review of Financial Studies* 32.5 (2019): hhz029.

Kim, Oliver, and Robert E. Verrecchia. "Trading volume and price reactions to public announcements." *Journal of Accounting Research* 29.2 (1991): 302-321.

Kim, Oliver, and Robert E. Verrecchia. "Market liquidity and volume around earnings announcements." *Journal of Accounting and Economics* 17.1-2 (1994): 41-67.

Kim, Oliver, and Robert E. Verrecchia. "Pre-announcement and event-period private information." *Journal of Accounting and Economics* 24.3 (1997): 395-419.

Koudijs, Peter. "Those who know most: Insider trading in eighteenth-century Amsterdam." *Journal of Political Economy* 123.6 (2015): 1356-1409.

Koudijs, Peter. "The boats that did not sail: Asset price volatility in a natural experiment." *The Journal of Finance* 71.3 (2016): 1185-1226.

Koshiw, Isobel. "How a Hacker Network Turned Stolen Press Releases into $100 Million." *The Verge,* 22 Aug. 2018, https://www.theverge.com/2018/8/22/17716622/sec-business-wire-hack-stolen-press-release-fraud-ukraine.

Kyle, Albert S. "Continuous auctions and insider trading." *Econometrica: Journal of the Econometric Society* (1985): 1315-1335.

Kyle, Albert S. "Informed speculation with imperfect competition." *The Review of Economic Studies* 56.3 (1989): 317-355.

Landsman, Wayne R., and Edward L. Maydew. "Has the information content of quarterly earnings announcements declined in the past three decades?." *Journal of Accounting Research* 40.3 (2002): 797-808.

Lee, Charles M.C., and Christina Zhu. "Active Funds and Bundled News" Working Paper Available at: https://www.gsb.stanford.edu/faculty-research/working-papers/active-funds-bundled-news

McNichols, Maureen, and Brett Trueman. "Public disclosure, private information collection, and short-term trading." *Journal of Accounting and Economics* 17.1-2 (1994): 69-94.

Meulbroek, Lisa K. "An empirical analysis of illegal insider trading." *The Journal of Finance* 47.5 (1992): 1661-1699.

Pankoff, Lyn D., and Robert L. Virgil. "Some preliminary findings from a laboratory experiment on the usefulness of financial accounting information to security analysts." *Journal of Accounting Research* (1970): 1-48.

Piotroski, Joseph D., and Darren T. Roulstone. "The influence of analysts, institutional investors, and insiders on the incorporation of market, industry, and firm-specific information into stock prices." *The Accounting Review* 79.4 (2004): 1119-1151.

The Securities Exchange Act of 1934. 17 C.F.R. § 240.10b-5 2000

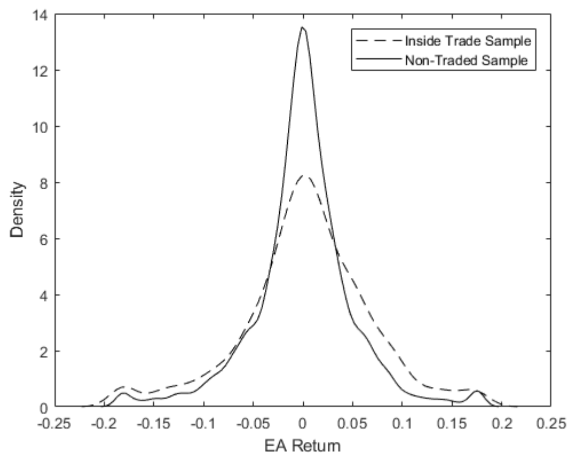
"SEC Charges 32 Defendants in Scheme to Trade on Hacked News Releases." U.S. Securities and Exchange Commission, 11 Aug. 2015, https://www.sec.gov/news/pressrelease/2015-163.html.

"What We Do." U.S. Securities and Exchange Commission, 10 June 2013, https://www.sec.gov/Article/whatwedo.html.

Figure 1: Distribution of Informed-Traded Earnings Announcement Returns

Figure 1 plots the distribution of earnings announcement returns for the informed-traded sample and the non-traded sample. The plotted distributions are kernel densities using the optimal mean square error Epanechnikov kernel. In Panel A, the non-traded sample is a constructed through liquidity matching. Liquidity is measured as the dollar-volume for the 1-month prior to the earnings announcement. The non-traded liquidity matched sample is of the 3 earnings announcements with the most similar dollar volume within the same week. In Panel B, I split the sample into quintiles of liquidity for each quarter. For each quintile of liquidity, I plot the distribution of earnings announcement returns by group: inside-traded and not inside-traded.

Panel A. Liquidity Matched



Panel B. Liquidity Quintiles

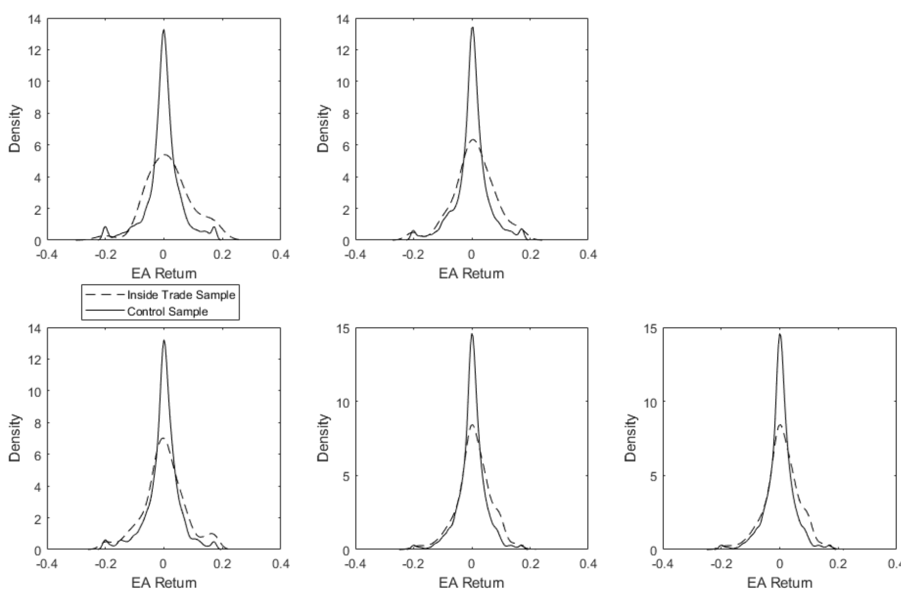
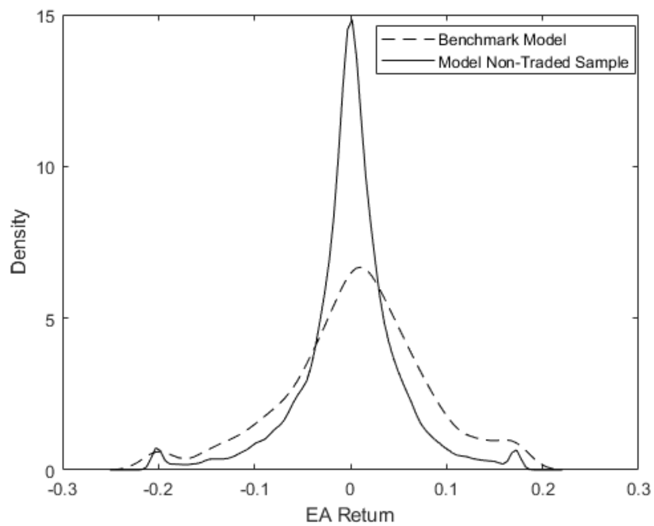


Figure 2: Distribution of Benchmark Model Earnings Announcement Returns

Figure 2 plots the distribution of earnings announcement returns for the benchmark model. The benchmark model chooses the earnings announcement with the largest earnings surprise multiplied by a historically estimated earnings response coefficient (equation (15)). The benchmark model is constrained to choose the same number of earnings announcements by quarter-liquidity quintile group. The plotted distributions are kernel densities using the optimal mean square error Epanechnikov kernel. Panel A plots the kernel density of benchmark model earnings announcement returns. Panel B plots the difference in the kernel densities of Figure 1 Panel A and Figure 2 Panel A, illustrating the relative performance of the informed traders and benchmark model. The benchmark model performed marginally better because more positive mass is in the tails than that of the informed traders.

Panel A: Benchmark Model Performance



Panel B: Comparison of Performance: Benchmark Model vs. Informed Traders

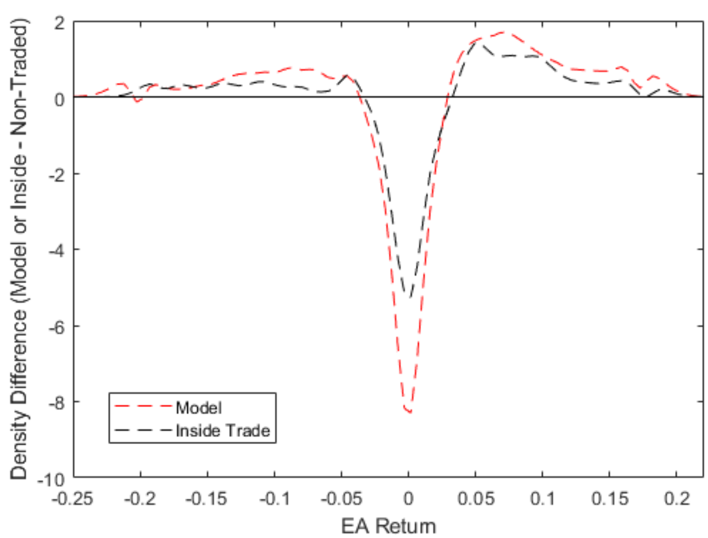


Figure 3: Endogenous Effects of Informed Trade on Earnings Announcement Returns

Figure 3 illustrates the endogenous effects of informed trade on earnings announcement returns. Suppose that the earnings announcement is publicly available at 4pm and contains positive information about firm fundamentals. The informed traders gained access to the earnings announcement at 1pm and traded on the information between 1pm and 4pm. The price impact of the informed traders is the difference in P_{1pm} and P_{4pm}. Depending on whether the market correctly infers that the informed traders have already partially priced the earnings announcement information, the realized price will be between $p^T_{t+1,9:30\ am}$ and $p^O_{t+1,9:30\ am}$. This positive bias to earnings announcement returns illustrates the endogeneity effect of informed trade.

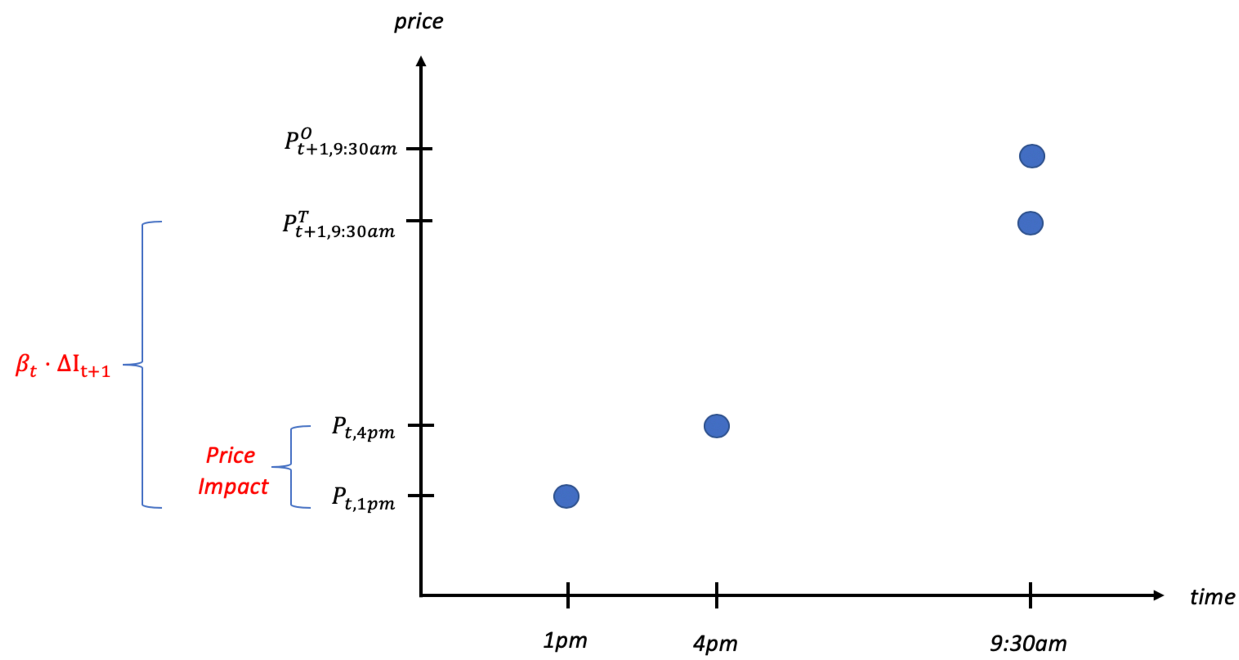


Table 1: Descriptive Statistics of Earnings Announcements

Panel A. Earnings Announcement Distribution Time by Informed Trade

Time is eastern standard time (EST). Pre-market is the time from 12:00 am to 9:30 am. Market hours are from 9:30 am to 4:00 pm. Post market is from 4:00 pm to 12:00 am. The earnings announcement time is sourced from Wall Street Horizons.

	Informed Trade	N	Probability	Difference in Probability	Mean	Standard Deviation	Median	1st Quartile	3rd Quartile
EA Distribution - Pre-Market	0	4,808	47.6%	20.2%***	7:15 am	1 hr 12 min	7:20 am	7:00 am	8:00 am
	1	282	27.4%		7:04 am	1 hr 13 min	7:00 am	6:30 am	7:55 am
EA Distribution - Market Hours	0	204	2.0%	1.7%***	12:47 pm	1 hr 57 min	12:35 pm	11:05 am	2:39 pm
	1	3	0.3%		2:26 pm	1 hr 17 min	2:47 pm	1:00 pm	3:30 pm
EA Distribution - Post-Market	0	5,105	50.5%	-21.8%***	4:28 pm	0 hr 46 min	4:06 pm	4:02 pm	4:31 pm
	1	744	72.3%		4:16 pm	0 hr 29 min	4:05 min	4:01 pm	4:15 pm

* p<0.1; ** p<0.05; *** p<0.01

Panel B. Earnings Announcement Fama-French 10 Industries by Informed Trade

The 10 Fama-French industry portfolios are described in the industry column and available on Fama and French's website.

	Industry	Informed Trade	N	Probability	Difference in Probability
1	Consumer Non-Durables – Food, Tobacco, Textiles, Apparel, Leather, Toys	0	437	4.33%	1.02%
		1	34	3.30%	
2	Consumer Durables – Cars, TV's, Furniture, Household Appliances	0	220	2.18%	-1.22%**
		1	35	3.40%	
3	Manufacturing – Machinery, Trucks, Planes, Chemicals, Off Furn, Paper, Com Printing	0	1,065	10.54%	-1.70%*
		1	126	12.24%	
4	Oil, Gas, and Coal Extraction and Products	0	540	5.35%	-0.68%
		1	62	6.03%	
5	Business Equipment – Computers, Software, and Electronic Equipment	0	1,857	18.39%	-13.98%***
		1	333	32.36%	
6	Telephone and Television Transmission	0	299	2.96%	1.70%***
		1	13	1.26%	
7	Wholesale, Retail, and Some Services (Laundries, Repair Shops)	0	711	7.04%	-4.53%***
		1	119	11.56%	
8	Healthcare, Medical Equipment, and Drugs	0	1,035	10.25%	2.67%***
		1	78	7.58%	
9	Utilities	0	369	3.65%	1.71%***
		1	20	1.94%	
10	Other – Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainment, Finance	0	3,563	35.28%	15.06%***
		1	208	20.21%	

* p<0.1; ** p<0.05; *** p<0.01

Panel C. Characteristics of Earnings Announcements by Informed Trade

See Appendix A for variable definitions and source.

	Informed Trade	N	Mean	Difference in Mean	Standard Deviation	Median	1st Quartile	3rd Quartile
$\lvert R_{i,t}\rvert$	0	10,072	3.79%	-1.4%***	5.01%	2.2%	0.9%	4.8%
	1	1,029	5.15%		4.8%	3.5%	1.5%	6.7%
$\lvert EPS_{i,t} - \overline{EPS}_{i,t}\rvert$	0	7,360	0.5%	0.1%***	1.0%	0.2%	0.1%	0.4%
	1	881	0.4%		0.8%	0.2%	0.1%	0.4%
$\lvert Rev_{i,t} - \overline{Rev}_{i,t}\rvert$	0	7,403	5.9%	1.0%***	9.2%	2.8%	1.2%	6.4%
	1	882	4.9%		7.2%	2.5%	1.1%	5.5%
Analyst Following	0	7,553	10	-3***	7.4	8	4	14
	1	885	13		8.5	11	7	18
Control Volume (mil)	0	10,100	41.8	-27.2***	92.7	7.9	1.2	35.0
	1	1,029	69.0		119.0	22.5	6.1	70.5
Abnormal Volume (mil)	0	10,100	0.82	-0.44***	1.3	0.45	0.04	1.11
	1	1,029	1.25		1.4	0.85	1.11	1.63
$G_{i,t}$	0	10,100	27.2%	-15.0%***				
	1	1,029	42.2%					

* p<0.1; ** p<0.05; *** p<0.01

Table 2 – Descriptive Statistics of the Informed Trader's Decisions

Panel A. Number of Inside Trades

	N	Percentage
Non-Traded	10,100	90.75%
Inside Trades	1,029	9.25%

Panel B. Time to Trade & Holding Period

	N	Mean	Standard Deviation	Median	1st Quartile	3rd Quartile
Max_TT	1029	13 hrs 55 min	18 hrs 58 min	6 hrs	3 hrs 9 min	18 hrs 38 min
TT	1029	6 hrs 46 min	11 hrs 43 min	1 hr 54 min	54 min	14 hrs 9 min
Holding	919	24 hrs 38 min	16 hrs 43 min	19 hrs 9 min	18 hrs 9 min	21 hrs 55 min

Panel C: Informed Trade Profitability

	N	Mean	Standard Deviation	Median	1st Quartile	3rd Quartile
$TD_{i,t}$	919	834.97	1,458.59	288.20	66.78	905.75
$PL_{i,t}$	919	33.81	143.71	2.61	-1.65	23.32
$RI_{i,t}$	919	3.16%	15.30%	2.0%	-1.2%	5.93%

Table 3: Profit Maximization and the Probability of Informed Trade

This table presents results of regressing the choice of insider trade (1 if the earnings announcement was traded, 0 if the earnings announcement was not traded) on the absolute value of realized earnings announcement returns and liquidity. Panel A presents the at-means marginal coefficients of a Logit model. Column (1) includes neither time nor industry fixed effects. Column (2) includes time fixed effects. Column (3) includes time and industry fixed effects. For ease of interpretation, the explanatory variables are standardized such that one unit is a standard deviation. A one standard deviation increase in realized earnings returns is associated with a 1.76 percentage points increase in the probability of informed trade (column (1)). This is a 19% increase relative to the unconditional sample probability of informed trade (9.25%). Standard errors are clustered by quarter. Panel B presents the estimated marginal effects at various percentiles of earnings return and liquidity: 10% (column (1)), 25% (column (2)), 75% (column (3)), 90% column (4).

$$\Pr(Y = 1) = \frac{1}{1 + e^{-W_{i,t}}} \tag{5}$$

$$W_i = \alpha + \beta_1 |R_{i,t}| + \beta_2 L_{i,t} + \beta_3 T_{i,t}$$

Panel A. At Means Marginal Effects

Inside Trade	(1)	(2)	(3)
$\lvert R_{i,t}\rvert$	1.7593***	1.6355***	1.1630***
	(0.2014)	(0.2458)	(0.234)
$L_{i,t}$	4.6024***	5.0545***	4.9100***
	(0.2484)	(0.4041)	(0.4225)
$T_{i,t}$	7.8519***	8.1138***	7.9516***
	(0.5540)	(0.7707)	(0.7379)
N	11,103	11,102	11,097
Pseudo R^2	8.51%	14.06%	15.85%
Time FE	N	Y	Y
Industry FE	N	N	Y

* p<0.1; ** p<0.05; *** p<0.01

Panel B. Baseline Specification at Various Percentiles of Return and Liquidity

Inside Trade	(1)	(2)	(3)	(4)
Percentile	10%	25%	75%	90%
$\lvert R_{i,t} \rvert$	0.6864***	1.0768***	2.6403***	3.6881***
	(0.1807)	(0.2313)	(0.4391)	(0.6147)
$L_{i,t}$	1.7956***	2.8168***	6.9071***	9.6480***
	(0.2892)	(0.3649)	(0.9719)	(1.4997)
$T_{i,t}$	3.0634***	4.8056***	11.7840***	16.4601***
	(0.8706)	(1.1003)	(1.753)	(2.1997)

* p<0.1; ** p<0.05; *** p<0.01

Table 4: Profit Maximization and Price Impact

This table presents results of regressing the price impact of informed traders on realized earnings announcement returns $(R_{i,t})$ and liquidity $(L_{i,t})$ and time to trade $(T_{i,t})$. Column (1) includes neither time nor industry fixed effects. Column (2) includes quarter fixed effects. Column (3) includes quarter and industry fixed effects. The coefficients report the at means marginal effects of the Logit model. For ease of interpretation, liquidity is standardized such that one unit is one standard deviation. However, $R_{i,t}$ is not because of the economically meaningful interpretation: a one percentage point increase in realized return is associated with an 8.52 bps increase in price impact. Standard errors are clustered by quarter.

$$\rho_{i,t} = \alpha + \beta_1 R_{i,t} + \beta_2 L_{i,t} + \beta_3 TT_{i,t} + \epsilon_{i,t} \tag{6}$$

Price Impact	(1)	(2)	(3)
$R_{i,t}$	0.0852***	0.0838***	0.0773***
	(0.0151)	(0.0157)	(0.017)
$L_{i,t}$	-0.4413***	-0.4581***	-0.4695***
	(0.0775)	(0.0804)	(0.0859)
$TT_{i,t}$	-0.1012***	-0.0977***	-0.0793***
	(0.0224)	(0.0288)	(0.0307)
N	1,026	1,026	1,025
R^2	14.23%	18.66%	20.00%
Time FE	N	Y	Y
Industry FE	N	N	Y

* p<0.1; ** p<0.05; *** p<0.01

Table 5 – Empirical and Simulated Moments

Table 5 estimates the empirical moments in equation (12) for each quarter from the data. These moments are computed for the informed traded earnings announcements. The moments include average realized earnings announcement return ($\bar{R}_t$), average liquidity ($\bar{L}_t$) and average return times liquidity ($\overline{RL}_t$). $\bar{R}_t = \frac{1}{X_t}\sum_i R_{i,t}$, $\bar{L}_t = \frac{1}{X_t}\sum_i L_{i,t}$, and $\overline{RL}_t = \frac{1}{X_t}\sum_i R_{i,t}L_{i,t}$ and for all i earnings announcements that were informed-traded. X_t is the total number of earnings announcements informed traded in quarter t. The simulated moments in equation (13) are estimated using model parameters described in Table 6. The accuracy of the model fit is measured as the difference between the empirical and simulated moments. The root-mean square errors of the simulated $\bar{R}_t$, $\bar{L}_t$, and $\overline{RL}_t$ moments are 0.07, 0.42, and 1.15 *seriatim*.

	Empirical Moments			Simulated Moments		
	(1)	(2)	(3)	(4)	(5)	(6)
	$\bar{R}_t$	$\bar{L}_t$	$\overline{RL}_t$	$\bar{R}_t$	$\bar{L}_t$	$\overline{RL}_t$
Q1 2011	5.58	15.25	83.24	5.58	15.21	83.56
Q2 2011	5.50	15.44	88.28	5.51	16.15	88.29
Q3 2011	5.10	16.66	84.02	5.11	16.92	84.32
Q4 2011	4.91	16.66	80.82	4.91	16.69	80.65
Q1 2012	4.60	16.77	75.32	4.58	17.10	76.40
Q2 2012	4.31	16.98	73.19	4.27	17.11	72.46
Q3 2012	4.17	16.22	67.37	4.11	17.16	69.08
Q1 2013	4.91	17.13	83.41	4.86	17.30	83.14
Q2 2013	4.56	16.28	73.37	4.51	16.58	74.34
Q3 2013	6.98	17.91	125.23	7.20	17.38	122.37
Q4 2013	5.95	17.28	106.08	6.03	17.80	106.11
Q4 2014	5.94	17.80	101.53	5.92	17.58	99.84
Q1 2015	5.19	17.59	90.32	5.20	17.70	89.68

Table 6: Model Parameter Estimates

Table 6 reports the model parameter estimates $(\beta_2, \beta_3, \sigma_\epsilon)$ from equation (14) for each quarter of the data. The coefficient β_1 is calibrated to equal 1 such that the interpretation of β_2 is the profit maximizing tradeoff between one unit of expected return conditional on signal s_i ($E[R|s_i]$) and one unit of liquidity (L_i). Liquidity is measured as the log dollar trading volume in the month prior to the earnings announcement and one unit is on average 0.41 standard deviations in the sample. The coefficient β_2 is on the interaction of expected return and liquidity. The coefficient σ_ϵ measures the noise in earnings announcement return signals.

Period	β_2	β_3	σ_ϵ
Q1 2011	-4.96***	4.20***	14.41***
	(0.1388)	(0.1013)	(0.461)
Q2 2011	2.12***	1.25***	11.55***
	(0.2239)	(0.1188)	(0.2206)
Q3 2011	2.24***	1.05***	15.05***
	(0.0358)	(0.0262)	(0.1743)
Q4 2011	0.41***	1.70***	24.02***
	(0.0041)	(0.0152)	(0.4568)
Q1 2012	1.89***	1.04***	19.11***
	(0.0584)	(0.0297)	(0.2765)
Q2 2012	0.64***	1.25***	27.59***
	(0.0085)	(0.0129)	(0.444)
Q3 2012	1.92***	1.07***	22.06***
	(0.1479)	(0.0673)	(0.8754)
Q1 2013	1.96***	1.13***	16.81***
	(0.0171)	(0.0078)	(0.1919)
Q2 2013	2.35***	1.11***	11.70***
	(0.1174)	(0.0458)	(0.2208)
Q3 2013	2.28***	1.10***	11.25***
	(0.0373)	(0.0216)	(0.0842)
Q4 2013	2.36***	1.29***	11.01***
	(0.016)	(0.0095)	(0.1701)
Q4 2014	2.39***	1.20***	9.26***
	(0.0126)	(0.0093)	(0.1361)
Q1 2015	4.77***	0.79***	10.84***
	(0.0455)	(0.0048)	(0.1063)

* p<0.1; ** p<0.05; *** p<0.01

Table 7: Informed Trade Covariance with Earnings Signals and Noise Estimates

Table 7 presents results of regressing the choice of insider trade (1 if the earnings announcement was traded, 0 if the earnings announcement was not traded) on a series of explanatory variables described in Section 5. The coefficients report the at means marginal effects of the Logit model. Standard errors are clustered by quarter.

$$P\,\mathrm{r}(Y=1) = \frac{1}{1+e^{-W_{i,t}}} \tag{24}$$

$$W_i = \alpha + \beta_1 D_{i,t} + \beta_2 Near_{i,t} + \beta_3 s_{i,t}^{agree} + \beta_4 G_{i,t} + \beta_5 GS_{i,t} + \beta_6 S_{i,t} + \beta_7 L_{i,t} + \beta_8 T_{i,t}$$

Inside Trade	(1)	(2)	(3)
$D_{i,t}$	-2.0137***	-1.7194***	-1.1583**
	(0.5611)	(0.4661)	(0.4851)
$Near_{i,t}$	-1.7476***	-1.9615***	-1.8523**
	(0.6729)	(0.6902)	(0.7308)
$s_{i,t}^{agree}$	3.6953***	3.2260***	3.0267***
	(1.3732)	(0.8638)	(0.8527)
$G_{i,t}$	2.3466***	2.1354***	1.3335*
	(0.8021)	(0.7278)	(0.7247)
$GS_{i,t}$	2.3228**	2.0718**	1.9866**
	(0.9914)	(0.8328)	(0.8281)
$S_{i,t}$	0.8015***	0.9112***	0.5976***
	(0.2047)	(0.1613)	(0.1442)
$L_{i,t}$	3.6742***	3.9757***	3.5004***
	(0.7878)	(0.6795)	(0.7011)
$T_{i,t}$	8.6452***	8.0466***	7.9413***
	(1.4259)	(0.8905)	(0.8706)
N	8,353	8,353	8,353
Pseudo R^2	8.16%	14.18%	15.63%
Time FE	N	Y	Y
Industry FE	N	N	Y

* $p<0.1$; ** $p<0.05$; *** $p<0.01$

Table 8: Informed Trader Profit-Loss and Return Autocorrelation

Table 8 presents estimates of autocorrelation coefficients for the profit and loss (PL_t) and return (R_t) of informed trades aggregated at the daily and weekly frequencies. Note that the return is not equal to the earnings announcement return ($R_{i,t}$). The profit and loss or return is what the informed traders are reported to have earned over all earnings announcements in period t. The autoregression specifications are

$$PL_t = \alpha + \sum_{\tau=1}^{3} \beta_\tau PL_{t-\tau} + \epsilon_t \tag{25}$$

$$R_t = \alpha + \sum_{\tau=1}^{3} \beta_\tau R_{t-\tau} + \epsilon_t \tag{26}$$

Standard errors are Newey-West corrected for three lags of autocorrelation. The autocorrelation coefficients tend to be either insignificant or positive, indicating a mild degree of positive autocorrelation.

	PL_t Daily	PL_t Weekly	R_t Daily	R_t Weekly
Variable	(1)	(2)	(3)	(4)
PL_{t-1}	0.038	0.293		
	(0.070)	(0.132)**		
PL_{t-2}	0.206	0.032		
	(0.124)*	(0.087)		
PL_{t-3}	0.018	0.182		
	(0.066)	(0.112)		
R_{t-1}			0.089	-0.038
			(0.112)	(0.111)
R_{t-2}			-0.020	-0.043
			(0.107)	(0.101)
R_{t-3}			0.082	0.242
			(0.090)	(0.084)***
N	216	68	216	68
R^2	0.05	0.28	0.01	0.09

* *p*<0.1; ** *p*<0.05; *** *p*<0.01

Table 9: Period-End Predictability of Informed Trader Profit-Loss and Return

Table 9 presents the OLS regression results of profit and loss (PL_t) or return (R_t) for the three earnings announcement trades prior to period-end on the total profit and loss $\left(\overline{PL}_{t,-}\right)$ or average return $(\bar{R}_{t,-})$ for the period (excluding the last three trades). Columns (1) and (3) present results at the weekly frequency and Columns (2) and (4) present results at the monthly frequency. Standard errors are heteroskedasticity robust.

$$PL_t = \alpha + \beta\overline{PL}_{t,-} + \epsilon_t \tag{27}$$

$$R_t = \alpha + \beta\bar{R}_{t,-} + \epsilon_t \tag{28}$$

The coefficients tend to be either insignificant or positive, indicating that period-end informed trader profit-loss and returns mildly positively covary with period performance leading up to the final three trades.

	PL_t Weekly	PL_t Monthly	R_t Weekly	R_t Monthly
Variable	(1)	(2)	(3)	(4)
$\overline{PL}_{t,-}$	0.006	0.019		
	(0.014)	(0.018)		
$\bar{R}_{t,-}$			0.145	0.467
			(0.227)	(0.188)**
N	92	90	92	90
R^2	0.00	0.04	0.00	0.07

* p<0.1; ** p<0.05; *** p<0.01

Table 10: Probability of Informed Trade and EA Returns and Liquidity (lower bound)

Table 10 is analogous to Table 3 Panel A but uses the endogeneity corrected absolute value earnings announcement returns $|\underline{R_{i,t}}|$. This table presents results of regressing the choice of insider trade (1 if the earnings announcement was traded, 0 if the earnings announcement was not traded) on endogeneity corrected absolute value of realized earnings announcement returns $|\underline{R_{i,t}}|$, and liquidity. Column (1) includes neither time nor industry fixed effects. Column (2) includes time fixed effects. Column (3) includes time and industry fixed effects. For ease of interpretation, the explanatory variables are standardized such that one unit is a standard deviation. The coefficients are the at-means marginal coefficients of the below specified Logit model. A one standard deviation increase in realized earnings returns is associated with a 1.62 percentage points increase in the probability of informed trade (column (1)). This is an 18% increase relative to the unconditional sample probability of informed trade (9.25%). Standard errors are clustered by quarter.

$$P\,r(Y = 1) = \frac{1}{1 + e^{-W_{i,t}}} \tag{29}$$

$$W_i = \alpha + \beta_1 |\underline{R_{i,t}}| + \beta_2 L_{i,t} + \beta_3 T_{i,t}$$

Inside Trade	(1)	(2)	(3)
$\lvert\underline{R_{i,t}}\rvert$	1.6165***	1.4814***	0.9248***
	(0.2084)	(0.2207)	(0.2074)
$L_{i,t}$	4.5653***	5.0400***	4.9489***
	(0.2598)	(0.4289)	(0.4506)
$T_{i,t}$	8.0460***	8.2896***	8.1332***
	(0.5726)	(0.8123)	(0.7696)
N	10,845	10,845	10,840
Pseudo R^2	7.99%	13.58%	15.42%
Time FE	N	Y	Y
Industry FE	N	N	Y

* p<0.1; ** p<0.05; *** p<0.01

Table 11: Price Impact and EA Returns and Liquidity (lower bound)

Table 11 is analogous to Table 4 but uses the endogeneity corrected earnings announcement returns $|\underline{R_{i,t}}|$, which exclude the informed trading period. These estimates present a lower bound to the covariance between price impact and earnings announcement returns. This table presents results of regressing the price impact of informed traders on endogeneity corrected realized earnings announcement returns $(R_{i,t})$ and liquidity $(L_{i,t})$ and time to trade $(T_{i,t})$. Column (1) includes neither time nor industry fixed effects. Column (2) includes quarter fixed effects. Column (3) includes quarter and industry fixed effects. The coefficients report the at means marginal effects of the Logit model. For ease of interpretation, liquidity is standardized such that one unit is one standard deviation. However, $\underline{R_{i,t}}$ is not because of the economically meaningful interpretation: a one percentage point increase in endogeneity corrected realized return is associated with a 4.59 bps increase in price impact. Standard errors are clustered by quarter.

$$\rho_{i,t} = \alpha + \beta_1 \underline{R_{i,t}} + \beta_2 L_{i,t} + \beta_3 TT_{i,t} + \epsilon_{i,t} \tag{30}$$

Price Impact	(1)	(2)	(3)
$\underline{R_{i,t}}$	0.0459***	0.0437***	0.0342**
	(0.0124)	(0.0135)	(0.015)
$L_{i,t}$	-0.4761***	-0.4971***	-0.5038***
	(0.0775)	(0.0808)	(0.0858)
$TT_{i,t}$	-0.1037***	-0.0992***	-0.0729**
	(0.027)	(0.0327)	(0.0313)
N	1026	1026	1025
R^2	9.00%	13.62%	15.63%
Time FE	N	Y	Y
Industry FE	N	N	Y

* p<0.1; ** p<0.05; *** p<0.01

Table 12: Robustness to Various Liquidity Controls

Table 12 estimates regression specification (5) for the sample split into quintiles of liquidity (L_q), where column (1) corresponds to the least liquid earnings announcements by quarter and column (5) corresponds to the most liquid. The proxy for liquidity varies by panel. For Panel A, the liquidity proxy is the 1-month average dollar volume prior to the earnings announcement. For Panel B, the liquidity proxy is the 1-month dollar-volume weighted bid-ask spread as a percentage of stock price.

$$P\,r\left(Y = 1 \middle| L_{i,t} \in L_q\right) = \frac{1}{1 + e^{-W_{i,t}}} \tag{31}$$

$$W_i = \alpha + \beta_1 |R_{i,t}| + \beta_2 T_{i,t}$$

Panel A. Dollar Volume Quintiles

Inside Trade	(1)	(2)	(3)	(4)	(5)
$\lvert R_{i,t} \rvert$	0.4537***	1.429651***	2.1838***	3.0053***	2.5747***
	(0.1763)	(0.3602)	(0.5028)	(0.6260)	(0.7026)
$T_{i,t}$	3.8876***	3.8499***	9.7077***	12.8013***	12.6043***
	(1.1046)	(1.1089)	(1.4431)	(1.4189)	(1.5268)
N	2,182	2,177	2,178	2,177	2,167
Pseudo R^2	5.65%	3.59%	3.51%	4.46%	4.90%
Informed Traded %	1.92%	6.43%	11.16%	12.45%	14.63%

* p<0.1; ** p<0.05; *** p<0.01

Panel B. Bid-Ask Spread Quintiles

Inside Trade	(1)	(2)	(3)	(4)	(5)
$\lvert R_{i,t} \rvert$	1.1830***	1.1148***	2.1083***	2.0051***	1.6279***
	(0.3721)	(0.5779)	(0.4221)	(0.5463)	(0.7240)
$T_{i,t}$	6.0967***	7.7844***	7.3938***	8.9745***	9.6619***
	(1.1046)	(1.8894)	(2.0802)	(1.7614)	(1.6622)
N	2,167	2,177	2,178	2,177	2,182
Pseudo R^2	5.65%	3.59%	3.51%	4.46%	4.90%
Informed Traded %	5.45%	9.23%	10.93%	10.75%	10.17%

* p<0.1; ** p<0.05; *** p<0.01