The Dynamics of Information Production and Diffusion:

Evidence from Buy-Side Participation in Earnings Conference Calls

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Abstract

We study information production and diffusion resulting from dynamic interactions between different types of investors in financial markets. With a theoretical framework based on the Q&A setting in earnings conference calls, we predict that information production in buy-side participation is more likely to trigger high price jumps and abnormal trading volume, as well as a subsequent price drift, relative to sell-side participation. Based on high-frequency trading data during earnings conference calls with synchronized transcripts and audios, we find evidence consistent with our prediction. The impact of buy-side participation on asset prices and trading activities is particularly strong when buy-side participants are affiliated with hedge funds. Our theoretical and empirical analyses shed light on how information complementarities affect financial market outcomes and provide an explanation to the "Einhorn Effect" that intrigues practitioners and policy makers.

Keywords: Information Production; Information Diffusion; Information Complementarity; Earnings Conference Calls

JEL Classification: G14, G30, M41

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1 Introduction

Information production and diffusion, as an outcome of dynamic interactions between different types of investors in financial markets, is one of the fundamental questions in finance.[1] Under this topic, one well-known and intriguing stylized fact is that information generated by some famous investors can instantaneously and significantly affect asset prices and trading activities. The "Einhorn Effect" is a good example. On the first day of May 2012, Herbalife held a conference call for sell-side analysts and buy-side investors. David Einhorn, a hedge fund manager who is famous for his bearish bet against Lehman Brother, asked managers a few questions about sales practices. Within five minutes before David concluded his questions by "Thanks so much, guys," Herbalife's stock price went down by 8.8%. When the market closed, Herbalife's stocks experienced a daily return of -20% and the daily trading volume was 15 times as high as that of the previous trading day. The impact of David's questions was not just short-lived: Herbalife's stock price went down for another 18% in the following week.[2]

While the "Einhorn effect" is well received, what are the underlying economic mechanisms through which information produced by buy-side investors triggers abnormal price changes, trading activities, and price drifts? More broadly, how market participants with different information interact with each other, and how differently the diverse information transmits to prices?

We address these questions by carrying out both theoretical and empirical analyses under a unique setting based on Q&A sessions of earnings conference calls, which are typically held within 48 hours after the earnings announcements. To the best of our knowledge, this is the only pubic verifiable and observable setting where participants with diverse information, including corporate managers, sell-side analysts, and buy-side institutions, interact with each other. This is also a rare setting where institutional investors can instantaneously optimize their trading decisions by learning private information from questions raised by sell-side analysts and other

[1]The seminal works on information production and diffusion in financial markets include Grossman and Stiglitz (1980), Kyle (1985, 1989), etc. Literature focusing on the interaction between different information include Admati and Pfleiderer (1987), Boot and Thakor (2001), Goldstein and Yang (2015, 2018), among others.

[2]See the story "A Might Wind: Sizing Up Fund Manager's Sway" on the Wall Street Journal (https://www.wsj.com/articles/SB10000872396390443720204578002362100327312).

buy-side institutions.

Under this setting, we first present a theoretical model with three important underlying assumptions. Our starting point is an assumption that the buy-side participants own more precise private information about the firm value than sell-side analysts. Relative to sell-side analysts, buy-side institutions bear a larger cost in participating earnings conference calls since other institutional investors may acquire information from their questions and front-run their investment ideas. When buy-side institutions ask questions in earnings conference calls, their participation per se signals that the benefit of confirming important private information has overwhelmed the cost of information leakage and front running. Therefore, we expect more precise information from buy-side participants.

Second, we incorporate underreaction in our economy by assuming that some investors ignore the information contained in the conference call; that is, only a fraction of investors are "newswatchers" as in Hong and Stein (1999).[3] The third assumption in our economy is about information complementarity. More specifically, we assume that after observing the disclosed information, the newswatchers produce their own private information in the next period. The information disclosed in the conference call is complementary to the private information in the sense that more precise information disclosure improves the information produced by newswatchers (e.g., Boot and Thakor, 2001).

Our model generates two empirical predictions. First, buy-side participation can trigger a larger price jump, a higher trading volume, and a higher return volatility than sell-side participation. This prediction is based on the economic intuition that investors put more weight on the new public information if it is more precise, and thus more new information is transmitted into the price, resulting in more pronounced price reactions. Second, our model predicts that buy-side participation can generate a stronger price drift relative to the situation where buy-side participation is absent. Information complementarity plays a key role in deriving this prediction.

[3]This is motivated by the well-known post-earnings announcement effect, which has been a necessary feature of our earnings announcement setting. Also, the literature usually attributes it to investors underreaction (e.g., Barberis et al., 1998; Daniel et al., 1998; Hong and Stein, 1999).

Specifically, more precise public information induces more efficient subsequent private information production, resulting in a stronger price drift.

We test our first prediction by using 2,216 within-trading-hour earnings conference calls with synchronized transcripts and audios. Our dataset allows us to match the duration of Q&As related to each call participant to high-frequency trading from TAQ database. Specifically, we divide trade hours of each trading day into 130 three-minute slots and we are able to identify all participants who speak up in each time slot. Consistent with the first prediction, we find that time slots associated with buy-side participation have a higher likelihood of experiencing price jumps and abnormal trading volumes, relative to time slots associated with sell-side participation. Based on the jump measure proposed in Lee and Mykland (2007), buy-side participation is associated with an increase of 5.3 percentage points in probability of price jumps relative to that for sell-side participation. This effect is both economically and statistically significant given that the average probability of price jump in time slots associated with sell-side participation is 4%. We further partition buy-side participants into subgroups and we find that the empirical pattern is particularly strong when the buy-side participation is contributed by a hedge fund.

We test our second prediction by using all earnings conference calls between 2003 and 2013. We partition all earnings conference calls in each quarter into five groups according to the earnings announcement returns between two days before to two days after the earnings announcement. We replicate the PEAD (i.e., post earnings announcement drift) effect by showing that firms in the top (bottom) quintile have positive (negative) price drifts subsequently, i.e., in a period from 3 trading days to 20 trading days after the earnings announcement. Consistent with the second prediction, if earnings conference calls after earnings announcements are participated by hedge fund participants, the magnitude of price drift increases by 75% and 85% for firms in the top and the bottom quintiles, respectively.

Our paper contributes to two strands of finance literature. First, we add to the understanding of diverse information and its interaction in financial markets. Admati and Pfleiderer (1987) firstly define whether two signals are complements or substitutes in predicting asset value, and study the viable information allocation given the information characteristics. Boot and Thakor (2001) decompose the many faces of information disclosure and examine the disclosure incentives of complementary/substitute information and its effects on investors' information acquisition. More recently, Goldstein and Yang (2015) consider a model where different traders are informed of different fundamentals and identify strategic complementarities in trading and acquisition between different information. Goldstein and Yang (2018) apply the similar multiple-dimension-uncertainty framework to study the effects of diverse information disclosure on the real efficiency. The study on diverse information and information interaction in financial markets is very relevant, but to our knowledge there is rarely direct empirical evidence. This is probably because it is usually hard to accurately identify different informed investors and thus, to attribute the market reactions to the information owned by different investors, let alone to study how different information interacts with each other. We fill this gap by presenting empirical evidence in a novel setting.

Second, we add to the literature on the information production in earnings conference calls. Bowen et al. (2002) suggest that earnings conference calls contain useful information that improves analysts' accuracy in forecasting earnings. Matsumoto et al. (2011) show that both sections in earnings conference calls, the managers' presentation section as well as the Q&A section, contain incremental information for investors and they find the Q&A section are relatively more informative than the presentation section. The most closely related paper to ours is Jung et al. (2017), who find that buy-side participation in earnings conference calls is associated with price changes, trading volume, institutional ownership, and short interest based on a call-level dataset. Taking advantage of high-frequency trading data with synchronized transcripts and audios of earnings conference calls, we address a serious endogeneity concern in previous studies: if we observe a correlation between buy-side participation and price jumps in a low frequency data, we cannot distinguish the explanation that the information related to buy-side participation triggers price jumps from an alternative story that the price jumps before earnings conference calls attract buy-side participation. However, in a high frequency setting, the second explanation is very unlikely. It is unlikely that a participant observes price jumps and then generates an idea within three minutes; even if that is possible, it is very unlikely that this participant can get a chance to ask questions in earnings conference calls within three minutes given that other participants have already lined up. Therefore, our tests relying on earnings conference call transcripts with synchronized audios and high-frequency trading data allow us to claim a causal link between information content within participants' questions and instantaneous price/volume reactions.

The paper proceeds as follows. Section 2 provides a theoretical framework that generates two empirical predictions. Section 3 discusses details of sample construction and summary statistics. Section 4 presents empirical tests of our two predictions. Section 5 concludes.

2 Theoretical Framework

2.1 The Model

This section presents a model to guide the specification and interpretation of our empirical results. Consider an economy which lasts for four periods: $t = 0, 1, 2$, and 3. Trade can occur in all periods. There are two assets: one bond with a risk-free return of zero and one risky stock that liquidates in Period 3 at the value of $\tilde{v}$, where $\tilde{v} \sim N(\bar{v}, \tau_v^{-1})$, and $\tau_v \in (0, \infty)$. The supply of the stock is normalized to zero.

In Period 1, there is an earning announcement and a conference call follows. A public signal $\tilde{y}$ is revealed:

$$\tilde{y} = \tilde{v} + \tilde{\eta}, \tag{1}$$

where $\tilde{\eta} \sim N\left(0, \tau_\eta^{-1}\right)$ and $\tilde{\eta}$ is independent of all other variables. When the question in the conference call is asked by a buy-side analyst, we assume the precision of the public signal is higher than when it is asked by a sell-side analyst. Since the information quality is captured by the signal-to-noise ratio τ_v/τ_η, we hereafter normalize τ_v to 1, keeping in mind that τ_η should be interpreted as information quality (i.e., signal-to-noise ratio).

Investors in the economy have constant-absolute-risk-aversion (CARA) utility with a risk-aversion coefficient γ. They are buy-and-hold investors who maximize expected terminal wealth: $E[-\exp(-\gamma \tilde{W}_3)]$, where $\tilde{W}_3$ is the terminal wealth in Period 3. There are two types of investors: $n = \{W, NW\}$, where n is the investor type, W denotes newswatchers, and NW denotes non-newswatchers. While the newswatchers (of mass $\lambda \in (0, 1)$) pay attention to the public signal $\tilde{y}$, the non-newswatchers (of mass $1 - \lambda$) just ignore it and end up being uninformed.

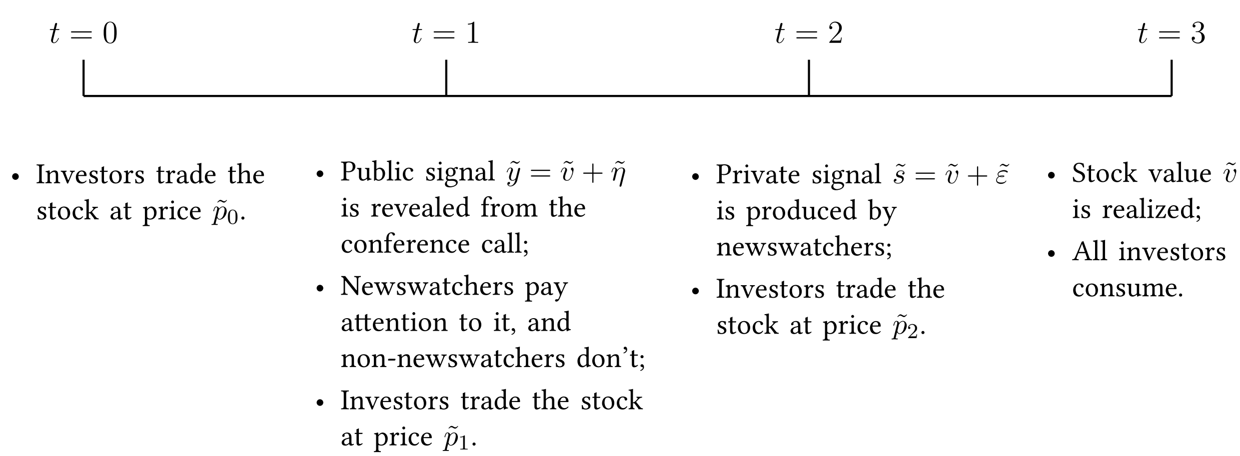
In Period 2, there is a piece of private information produced by newswatchers:

$$\tilde{s} = \tilde{v} + \tilde{\varepsilon}, \tag{2}$$

where $\tilde{\varepsilon} \sim N\left(0, (\alpha\tau_\eta)^{-1}\right)$ and $\alpha > 0$. The precision specification $\alpha\tau_\eta$ makes information $\tilde{y}$ complementary to $\tilde{s}$ in the sense that more precise $\tilde{y}$ improves the information production done by newswatchers in Period 2. This captures the idea that newswatchers analyze the information from the conference call and generate their new information afterwards (Boot and Thakor, 2001).

The timeline of the economy is as follows.

Figure 1: Timeline



To be transparent, we have three main assumptions. First, we assume that in the conference calls the buy-side owns more precise signals than the sell-side and thus, more precise signal is leaked when the buy-side asks questions in the conference call. This helps generate the cross-sectional difference between the buy-side and the sell-side questions. Secondly, some investors are assumed to neglect the public signal from the conference call. This serves as a device to generate under-reaction as in Hong and Stein (1999). Thirdly, more precise public information in the conference call helps more efficient information production afterwards in the sense that the new information is more precise, which is similar to the complementary information assumption in Boot and Thakor (2001).

2.2 Equilibrium Characterization

In Period 0, there is no information, so the two types of investors are identical and both demand zero units of stock. The equilibrium price is just the unconditional expected value of the stock: $\tilde{p}_0 = \bar{v}$. In Period 3, the stock is liquidated and all uncertainty is realized, so the stock price is equal to the realized uncertainty: $\tilde{p}_3 = \tilde{v}$.

We next solve for the demand of investors and equilibrium price in Periods 1 and 2. As is well known, the CARA-normal setup implies that the demand function of investor i of the type $n \in \{W, NW\}$ (newswatchers and non-newswatchers) in Period t is

$$D_n^{i,t} = \frac{1}{\gamma} \frac{E\left(\tilde{v}_t | \mathcal{F}_{n,t}\right) - \tilde{p}_t}{Var\left(\tilde{v}_t | \mathcal{F}_{n,t}\right)},\ t = 1, 2,$$

where $\mathcal{F}_{n,t}$ is the information set of the type n investor in Period t, and $\tilde{p}_t$ is the price of the stock in Period t.

Specifically, since the non-newswatchers ignore the public information in Period 1 (and thus generate no new information in Period 2), the demand of the non-newswatcher i in Period t is

$$D_{NW}^{i,t}\left(\tilde{p}_t\right) = \frac{E\left(\tilde{v}_0\right) - \tilde{p}_0}{\gamma Var\left(\tilde{v}_0\right)} = \frac{1}{\gamma}\left(\bar{v} - \tilde{p}_0\right),\ t = 1, 2.$$

In Period 1, newswatchers observe the public information and demand

$$D_W^{i,1}\left(\tilde{p}, \tilde{y}\right) = \frac{E\left(\tilde{v}|\tilde{y}\right) - \tilde{p}_1}{\gamma Var\left(\tilde{v}|\tilde{y}\right)} = \frac{1}{\gamma}\left[\bar{v} + \tau_\eta \tilde{y} - (1+\lambda\tau_\eta)\tilde{p}_1\right]. \tag{3}$$

In Period 2, newswatchers develop their own informaiton based on the analysis of the public information in Period 1 and demand

$$D_W^{i,2}\left(\tilde{p}_2, \tilde{y}, \tilde{s}\right) = \frac{1}{\gamma}\frac{E\left(\tilde{v}|\tilde{y}, \tilde{s}\right) - \tilde{p}_2}{Var\left(\tilde{v}|\tilde{y}, \tilde{s}\right)} = \frac{1}{\gamma}\{\bar{v} + \lambda\tau_\eta(\tilde{y} + \alpha\tilde{s}) - [1 + (1+\alpha)\lambda\tau_\eta]\tilde{p}_2\}. \tag{4}$$

In Period t, the stock market clears in equilibrium. That is,

$$\int_0^\lambda D_W^{i,t} di + \int_\lambda^1 D_{NW}^{i,t} di = 0,\ t = 1, 2, \tag{5}$$

which states that the total stock demand from the two types of investors is equal to the total supply (which is normalized to 0). Substituting the demand functions of the newswatchers and non-newswatchers in Period t into (5), we can compute the equilibrium price $\tilde{p}_1$ and $\tilde{p}_2$. We summarize the equilibrium prices in each period using the following proposition.

Proposition 1. *There exists a unique price in each period to clear the financial market, which is given by:*

$$\tilde{p}_0 = \bar{v} \tag{6}$$

$$\tilde{p}_1 = \frac{\bar{v} + \lambda\tau_\eta\tilde{y}}{1 + \lambda\tau_\eta}, \tag{7}$$

$$\tilde{p}_2 = \frac{\bar{v} + \lambda\tau_\eta\left(\tilde{y} + \alpha\tilde{s}\right)}{1 + \lambda\tau_\eta\left(1 + \alpha\right)}. \tag{8}$$

$$\tilde{p}_3 = \tilde{v} \tag{9}$$

2.3 Empirical Predictions

We next study real-time stock market reactions to the conference call by focusing on the period $t = 0$ to $t = 1$. Specifically we examine a variety of market outcomes: price jump, trading volume, and return volatility.

Price Jump. In Period 1, with the new public information, price of the risky asset jumps from $\tilde{p}_0$ to $\tilde{p}_1$. Since $\tilde{p}_1$ is a random variable depending on the realization of signal $\tilde{y}$, we use

$$JUMP \equiv \frac{\partial \left(\tilde{p}_1 - \tilde{p}_0 \right)}{\partial \tilde{y}} = \frac{\lambda \tau_\eta}{1 + \lambda \tau_\eta}$$

to capture the price jump. We find that when it is buy-side analyst who asks questions (i.e., τ_η is high), there is a larger price jump: $\frac{\partial JUMP}{\partial \tau_\eta} > 0$. The reason is that when the public information is more precise, newswatchers put more weight on the public signal in their demand functions, which transmits more information into the price and triggers a larger price jump.

Trading Volume. In Period 1, trading arises because of the arrival of the new public information and it occurs between newswatchers and non-newswatchers. We thus can measure trading volume by focusing only on the change of the stock demand of newswatchers from $t = 0$ to $t = 1$. Given that there is no demand for newswatchers in Period 0, trading volume can thus be measured as

$$TradeVol \equiv E\left(\left| \int_0^\lambda D_W^{i,1} \left(\tilde{p}_1, \tilde{y} \right) di \right| \right) = \sqrt{\frac{2}{\pi}} \frac{\lambda \left(1 - \lambda\right)}{\gamma \left(1 + \lambda \tau_\eta\right)} \sqrt{\tau_\eta \left(1 + \tau_\eta\right)}.$$

We find that if it is the buy-side analyst who asks questions (i.e., τ_η is high), there is a larger trading volume in the stock market: $\frac{\partial TradeVol}{\partial \tau_\eta} > 0$. This is because when the public signal is more precise, newswatchers pay more attention to it, resulting in more trading between newswatchers and non-newswatchers. Thus we can observe higher trading volume.

Return Volatility. From $t = 0$ to $t = 1$, the return of the stock is $\tilde{p}_1 - \tilde{p}_0$ and thus, the return volatility is given by

$$RetVol \equiv \sigma\left(\tilde{p}_1 - \tilde{p}_0\right) = \frac{\lambda}{1+\lambda\tau_\eta}\sqrt{\tau_\eta(1+\tau_\eta)}.$$

We find that when the buy-side analyst asks questions (i.e., τ_η is high), the return volatility is higher: $\frac{\partial RetVol}{\partial \tau_\eta} > 0$. This is consistent with the larger price jump and the higher trading volume as discussed above, all of which arise because more precise information triggers more pronounced price reactions in the financial market.

Prediction 1 (Price jump, trading volume, and return volatility) *When the buy-side asks questions in the conference call, there are (i) a larger price jump, (ii) a higher trading volume, and (iii) a higher return volatility.*

Price Drift. Following Banerjee, Kaniel and Kremer (2009), we say that the price exhibit price drift (reversal) if $E\left(\tilde{p}_2 - \tilde{p}_1 | \tilde{p}_1 - \tilde{p}_0\right)$ is increasing (decresing, respectively) in $\tilde{p}_1 - \tilde{p}_0$. That is, if $E\left(\tilde{p}_2 - \tilde{p}_1 | \tilde{p}_1 - \tilde{p}_0\right) = k\left(\tilde{p}_1 - \tilde{p}_0\right)$ for some positive (negative) value k, then prices exhibit drift (reversal). We can compute k as follows

$$k = \frac{\alpha\tau_\eta(1-\lambda)}{(1+\tau_\eta)[1+\lambda\tau_\eta(1+\alpha)]} > 0.$$

Thus, there is a price drift in our economy. This is due to inattention of the investors: only a fraction λ of investors pay attention to the public information from the conference calls, which prevents price from fully responding to the new information.

Whether the buy-side questions (i.e., high τ_η) can trigger stronger price drift in this economy? In other words, whether the buy-side questions can produce relatively higher expected returns following positive return in the last period (i.e., $\tilde{p}_1 > \tilde{p}_0$) and relatively lower expected returns following negative return in the last period (i.e., $\tilde{p}_1 < \tilde{p}_0$)? The common wisdom suggests that given a piece of new information, if the immediate price reactions to the information is stronger, the post-information drift should be weaker. However, this is not necessarily the case in an economy where there exists information interaction.

Formally we examine the effect of public signal precision τ_η on the price drift by taking derivative of k with respect to τ_η as follows:

$$\frac{\partial k}{\partial \tau_\eta} = \frac{\alpha (1-\lambda) \left[1 - \lambda \tau_\eta^2 (1+\alpha)\right]}{(1+\tau_\eta)^2 \left[1 + \lambda (\alpha + \tau_\eta)\right]^2} > (<)\, 0 \text{ when } \lambda (1+\alpha) < (>) \frac{1}{\tau_\eta^2}.$$

Thus, when there are not many newswatchers in the economy (i.e., a low λ), and/or when the information complementarity is low (i.e., a low α), more precise public signal in Period 1 would not weaken the post-earnings announcement drift, but instead strengthen it. The key driving forces behind this result are as follows. First, there is under-reaction in the market due to limited attention paid to the conference call (i.e., $\lambda < 1$). The lower the fraction of the newswatchers in the economy, the less information is impounded into price in Period 1 and thus, there is more profit opportunity left in Period 2. Second, the public signal $\tilde{y}$ triggers new information production in Period 2. The more precise $\tilde{y}$ is, the more precise information is produced (i.e., $\alpha > 0$). This suggests that newswatchers in Period 3 can trade more aggressively on the newly-produced private information after observing more precise information in the conference call, which contributes to the stronger price drift. Taken together, buy-side questions can trigger even stronger price drift due to the investors' behavior bias (under-reaction) and information complementarity.

Prediction 2 (Price drift) *There is a price drift after the conference call. When there are not many newswatchers or when the information complementariy is low (but not zero), the buy-side questions can produce relatively higher expected returns following positive returns and relatively lower expected returns following negative returns.*

3 Data and Sample Characteristics

3.1 Data Sources

Our study relies on three main data sources: 1) audios of earnings conference calls from EarningsCast.com; 2) transcripts of earnings conference calls from Reuters StreetEvents; and 3) intraday transaction data from NYSE Trade and Quote (TAQ) database.

We start with a sample of all 13,584 earnings conference calls from StreetEvents between January 2012 and March 2013. Since our study focuses on trading activities during the Q&A sessions of earnings conference calls, we require that the Q&A sessions of earnings conference calls must be held during trading hours, e.g., between 9:30AM and 4:00PM ET for stocks listed in NYSE, AMEX and NASDAQ. As a consequence we first exclude 5,949 calls where a part or the entire Q&A sessions of conference calls are held outside trading hours. Among all remaining 7,635 calls whose Q&A sessions are held during trading hours, we are able to purchase audios for 2,246 of them from EarningsCast.com.

In a typical earnings conference call, there is a waiting period of a few minutes between the scheduled starting time and the actual starting time, when managers get ready for the presentation. Audio tapes from other sources, e.g., corporate websites, typically truncate the waiting period. Therefore, researchers cannot identify the exact starting time of a conference call by using audio tapes from these sources. Audios that we purchase from EarningsCast.com are recorded from the scheduled starting time and the waiting periods of earnings conference calls have not been truncated. Therefore, these audio files allow us to compute the actual starting time of each earnings conference call accurately, which is typically 2 to 3 minutes later than the scheduled starting time. The accuracy in recording the starting time of earning conference calls is crucial for us to synchronize talks in earnings conference calls with high-frequency trading activities in financial markets. After the synchronization process, we are able to identify the starting and the end time of each sentence and as well as the exact duration of each Q&A exchange between one participant and managers.

Among 2,246 calls with audios, we are not able to synchronize 30 of them due to missing records in transcripts (e.g., some sentences in audios have not been recorded in corresponding transcripts). All screening criteria yield a final sample of 2,216 earnings conference calls with synchronized audios during trading hours.

In the table reported in Appendix III, we compare firm-quarters corresponding the 2,216 earnings conference calls with synchronized audios ("synchronized sample") with the "full sample" (i.e., firm-quarters corresponding to all 13,584 earnings conference calls held within our sample period) as well as the "trading-hour subsample" where Q&A sessions of earnings conference calls are held during trading hours. We find that firms in "synchronized sample" have higher return on asset and book-to-market ratios than those in the "full sample." However, we do not observe any significant difference in firm size, analyst coverage, and total analyst participation of earnings conference calls across all three samples. This mitigates the concern that the "synchronized sample" only represents earnings conference calls of very large firms, relative to those held by average firms in the full sample.

3.2 Participations of Earnings Conference Calls

There are, on average, 7.3 participants in each earnings conference call in our "synchronized sample." Among these participants, most of them, i.e., 91.52% of all participants, are sell-side analysts. 7.14% of all participants are buy-side analysts from various types of financial institutions and the remaining 1.34% of them are journalists from financial media.

Not surprisingly, most participants of earnings conference calls are sell-side analysts from investment banks. Attending earnings conference calls is an essential component of sell-side analysts' routine tasks. By raising questions in earnings conference calls, analysts are able to collect and verify information from management, to improve their accuracy in earnings forecasts (Bowen et al., 2002). Further, participations of earnings conference calls help analysts signal their reputation/skill as well as connectivity to the management in the labor market (Cen et al., 2017). As suggested in Table 1, each sell-side analyst, on average, asks 4.3 questions that contain 167.6

words. Questions from each analyst are answered by 1.9 managers with 390.7 words in replies. On average, it takes 216.4 seconds for a sell-side analyst to raise questions and receive replies in earnings conference calls.

[Insert Table 1 Here]

Relative to sell-side analysts' economic incentives to participate earnings conference calls, it is still unclear why buy-side analysts would like to show up and ask questions in earnings conference calls. One potential benefit is that buy-side analysts can confirm their private information in a public domain where managers are liable for all information they deliver in their answers. However, on the other hand, buy-side institutions bear a large cost associated with a potential chance of leaking their private information to other financial institutions while they raise questions in earnings conference calls.

We divide all buy-side institutions that participate earnings conference calls into three groups. We classify hedge funds by using the hedge fund list applied in Agarwal et al. (2013). We classify mutual funds by using the lists retrieved from CRSP Mutual Fund Database as well as Morningstar Mutual Fund Database. All remaining buy-side institutions, including private equities, venture capitals, university endowments, trusts, and individual investors are classified into the "others" group.

In Table 1, we also report summary statistics for each buy-side sub-group. Among all three sub-groups, buy-side analysts from hedge funds participate earnings conference calls most actively. Specifically, around 52% of all buy-side participants (i.e., 3.72% of all participants) work for hedge funds and 24% of them work for mutual funds. We observe three interesting patterns from summary statistics in Table 1. First, buy-side participants in all sub-groups tend to ask later questions in earnings conference calls relative to sell-side participants. Second, although they ask later than sell-side analysts, they have more questions and longer questions (in terms of number of words). Third, one would expect that longer questions have longer replies, as we observe for questions from mutual fund and other buy-side participants. However, questions from hedge fund participants, although they are longer than those from sell-side participants, receive shorter replies.

[Insert Table 2 Here]

For the three patterns observed in univariate comparison above, one possibility is that these relationships are driven by differences across earnings conference calls. In Table 2, we formalize these three patterns in multivariate regressions, where we are able to control for call fixed effects in all test specifications. As a consequence, our results in Table 2 are mainly driven by within-call variations in participant characteristics.

Column (1) of Panel A suggests that, after controlling for call fixed effect, the *sequence* of an average buy-side participant is on average 0.27 larger than an average sell-side analyst. This is consistent with our previous observation that buy-side analysts ask questions much later than sell-side analysts. There are two non-mutually exclusive explanations for this observation. Sell-side analysts, who typically cover a limited number of firms within one industry, have a strong economic incentive to build good connections with firms. In earnings conference calls, corporate managers are able to pick the most favorable sell-side analysts as early question raisers, to set the friendly and optimistic tone (Mayew, 2008; Cohen et al., 2016; Cen et al., 2017). Buy-side institutions manage portfolios that comprise a number of stocks and they have no economic incentive to please managers of specific firms. While managers have to take questions from buy-side participants given they are existing or potential shareholders, managers also understand that questions from the buy-side are likely much less friendly than the sell-side and, therefore, take questions from the buy side later. On the other hand, buy-side institutions face a much higher cost of raising questions in earnings conference calls. To minimize the possibility that other institution investors follow up their questions and front-run the information contained in their questions, buy-side participants may voluntarily push back their questions to the end of Q&A sessions.

In column (2), we report our analysis for the number of words in questions of each participant, i.e., the length of questions. Since later participants can follow up early questions by using "following up X's question" without repeating details again, we expect later questions are mechanically shorter. This is confirmed by the significant and negative coefficient of *Sequence* in column (2). After controlling for the sequence of questions, we find that the questions of an average buy-side participant has 15 words more than those from a sell-side analyst. In column (3), we analyze the correlation between the number of words in replies from managers and the identity of conference call participants. We control for the sequence and the number of words in each participant's questions and find that buy-side participants receive shorter replies from managers. On average, replies from managers to a buy-side participant's questions are 28 words shorter than those for questions of a sell-side analyst, suggesting some reluctance for managers to elaborate in their replies.

In Panel B of Table 2, we partition buy-side participants into three sub-groups. We observe that the pattern related to the sequence of questions are driven by all three sub-groups. The pattern related to the length of questions is solely driven by buy-side participants from mutual funds, i.e., hedge fund participants and other buy-side participants do not ask longer questions than sell-side participants. Further, managers' reluctance in providing detailed replies only apply to hedge funds and other buy-side institutions.

4 Empirical Results

4.1 Sample Construction

To test our theoretical predictions, the main challenge is to measure price jump, trading volume, and return volatility instantaneously when call participants are asking questions and receiving replies (from managers) in earnings conference calls. Previous studies based on low-frequency data, e.g., at a daily frequency, cannot address the following endogeneity issue: if we observe a correlation between price jumps and buy-side participations of earnings conference calls at a daily frequency, we cannot distinguish the explanation that the information disclosed in buy-side participations interacts with information of other investors and triggers price jumps from an alternative story that the price jumps before earnings conference calls attract buy-side participations. However, when we investigate this correlation based on high-frequency data (e.g., within a three-minute slot), the alternative explanation above is very unlikely: it is unlikely that a participant observes price jumps and then generates an idea within three minutes; even if that is possible, it is extremely unlikely that this participant can get a chance to ask questions in earnings conference calls within three minutes given that other participants have already lined up. Therefore, our tests relying on earnings conference call transcripts with synchronized audios and high-frequency trading data allow us to claim a causal link between information content within participantsfi questions and instantaneous price/volume reactions.

To organize our main test sample, one intuitive way is to partition trading slots according to the duration of questions and answers related to each participant. However, there exists a large variation in the duration of Q&As across all participants, i.e., some participants complete their Q&As in one minute and Q&As of others may last for five minutes. Therefore, under this setup, we are not able to compare trading activities, such as the likelihood of price jump, trading volume as well as return volatility across observations of different durations. Instead, we divide trading hours into time slots of equal durations. Specifically, for each trading day corresponding to a conference call in our sample, we divide trading hours of each trading day, i.e., from 9:30am to 4:00pm, into 130 three-minute slots. Our key independent variables, such as *Q&A: Buy Side* and *Q&A: Sell Side*, reflect whether a buy-side analyst or a sell-side analyst is asking questions or receive answers within a particular time slot. Under this setup, it is possible that a three-minute slot is participated by multiple questions raisers, e.g., one sell-side analyst and one buy-side analyst. In this case, both dummy variables, *Q&A: Buy Side* and *Q&A: Sell Side*, are equal to 1. Matsumoto et al. (2011) suggest that *managers' presentations* in the first part of earnings conference calls also contain information that has significant impacts on stock prices. Therefore, we also include a control variable, *Manager's Presentation*, to capture time slots associated with the presentation of managers. Finally, we add two independent variables, *Market Open* and *Market Close*, to capture abnormal trading activities frequently observed at the beginning and the end of each trading day. Detailed definitions of all control variables are provided in Appendix I. After we include all control variables, the benchmark in our tests is a time slot that is not within the duration of an earnings conference call and not at the market open or the market close of the trading day.

When a time slot is too short, it may not be able to capture trading activities as a response to information in Q&As of call participants; when a time slot is too long, there might be multiple participants associated with one time slot so that it is difficult to attribute price jumps to specific participants accurately. Given that the average duration of Q&As of one participant is 214.8 seconds, we employ a three-minute slot as the basic unit (i.e., one observation) in our main specification after trading off the costs and the benefits of using shorter or longer time slots. In unreported robustness checks, we replicate our results by using two-minute slots or four-minute slots and our results remain unchanged.

4.2 Prediction 1: Price Jump, Trading Volume and Return Volatility

Following Lee and Mykland (2007), we calculate stock returns by taking differences of log transaction prices. We construct three measures for project jumps. The first measure, the absolute stock returns (|Ret|), is a continuous measure without cutoffs. In addition to this continuous measure, we have two indicator variables representing price jumps. The first one is a jump measure based on Lee and Mykland (2007) that provide a model-free detection technique in identifying price jumps. The second one is a jump measure based on a universal cutoff level. Specifically, this indicator variable equals 1 if the absolute stock return of a three-minute slot is larger than 1%, and zero otherwise. For the trading volume measure, we first calculate dollar trading volumes by aggregating all trades within each three-minute slot. Since trading volume is persistent and closely related to firm size, we measure trading volume in our study by an adjusted volume measure (*Adj. Vol*), which is the dollar trading volume of a time slot standardized by the average dollar trading volume of all three-minute slots for the same stock in the previous month. We also construct two within-slot volatility measures for each three-minute slot. We first compute stock returns for each thirty-second slot. The first volatility measure, $Log(1+\sum Ret^2)$, is the natural logarithm of one plus the sum of squared returns of all 6 thirty-second slots within a three-minute slot. The second volatility measure, $Log(1+STD)$, is the natural logarithm of one plus the standard deviation of 6 thirty-second slots within a three-minute slot. For continuous dependent variables, we adopt OLS models with call fixed effects. Therefore, the coefficients exhibit within-call variations in price jumps, trading volumes and return volatilities when different call participants speak up. For binary dependent variables, we adopt both linear probability models with call fixed effects as well as logit models without call fixed effects.[4] Standard errors of all test specifications are clustered at the call level.

[Insert Table 3 Here]

Table 3 reports the average values of key variables for time slots associated with different participants. For all 288,080 three-minute slots in our sample, 17,405 slots are associated with managers' presentations and 22,130 time slots are associated with Q&As between participants and managers. Among these 22,130 time slots, sell-side analysts participate 93.6% of them and buy-side analysts participate 10.3% of them. For time slots related to buy-side institutions, more than half of them (i.e., 52.4%) are participated by hedge funds. Buy-side participation is associated with significant changes in stock prices. Further, there exists a large dispersion of impact across different types of buy-side institutions. For example, the average absolute return of time slots related to hedge fund participation is 0.283%, which is higher than that for time slots related to sell-side participation. While both average absolute returns of time slots related to mutual fund participation and other buy-side participation are lower than that of time slots related to sell-side participation. We observe a similar pattern based on both binary jump measures. Specifically, 12.5% and 7% of time slots associated with hedge fund participation experience price jumps based on the Lee and Mykland (2007) approach and the 1% cut-off, which are much higher than those for time slots related to sell-side participation. Based on the adjusted trading volume, we observe that time slots associated with participations of both hedge funds and mutual funds experience

[4]See Greene (2005) for various concerns of using fixed effects in estimating nonlinear models with limited dependent variables.

more active trading activities than those associated with sell-side participation. For time slots associated with hedge (mutual) fund participation, the average adjusted trading volume is 3.66 (3.47). This suggests that, when a hedge (mutual) fund participant asks questions and receive replies in one time slot, the trading volume within this time slot is 3.66 (3.47) times of the average trading volume for a three-minute slot in a one-month period preceding the earnings conference call. For time slots participated by sell-side analysts, the average adjusted volume is 2.31. We do not observe a clear pattern while comparing within-slot return volatility between slots participated by sell-side analysts and different types of buy-side participants. In fact, $Log(1 + STD)$ of time slots associated with all types of buy-side participants are lower than that of time slots associated with sell-side participation.

[Insert Table 4 Here]

Results of multivariate regressions on price jump, trading volume, and return volatility are reported in Table 4. The dependent variable in Column (1) of Panel A is the absolute value of stock returns in each three-minute slot. After controlling for the call fixed effects, we find that time slots participated by both sell-side and buy-side participants have higher absolute stock returns relative to those of the benchmark period, i.e., time slots outside earnings conference calls of the same trading day. Specifically, the average absolute stock return of the time slots associated with buy-side (sell-side) participation is 0.046% (0.056%) higher than that of benchmark periods. For both binary variables on price jumps, we carry out both logit models and linear probability models. We include call fixed effects when linear probability models are estimated. Based on the jump measure in Lee and Mykland (2007), estimates from both logit models and linear probability models suggest that time slots associated with buy-side participation have a much higher probability of experiencing price jumps than benchmark periods. Based on the estimate reported in Column (3), the difference of probability in experiencing price jumps between time slots with buy-side participation and time slots in the benchmark period is 6.5 percentage points, which is statistically significant at the 1% level. Consistent with Prediction 1, our test also suggests that time slots associated with buy-side participation have a much higher probability of experiencing price jumps than time slots associated with sell-side participation, i.e., the difference of probability in experiencing price jumps between time slots with buy-side participation and time slots of sell-side participation is 5.3 percentage points, which is also statistically significant at the 1% level. The jump measure based on the 1% cutoff generates a similar message that information production in time slots associated with buy-side and sell-side participation is more active than that in benchmark periods. However, the difference between the buy-side slots and the sell-side slots is much smaller under this measure.

Column (7) of Panel A reports the result based on adjusted trading volume. Both time slots associated with buy-side and sell-side participations have much higher adjusted trading volume than that of benchmark periods. Consistent with Prediction 1, the adjusted trading volume of time slots associated with buy-side participation is higher than that of time slots associated with sell-side participation. The difference, 0.804, is both economically and statistically significant. In Columns (7) and (8), we report our results related to within-slot return volatility. We show that time slots associated with both buy-side and sell-side participations have higher within-slot return volatilities than that of benchmark periods. However, both measures suggest that the within-period volatility of time slots associated with sell-side participation is higher than that of time slots associated with buy-side participation.

In Panel B, we "decompose" buy-side participation into participations of hedge funds, mutual funds, and other buy-side institutions. We find that the high association between price jump, adjusted trading volume and buy-side participation in Panel A is mainly driven by the participation of hedge funds. For example, in Column (4), we report the difference in the likelihood of price jumps between time slots associated with hedge fund participation and time slots associated with another group of participants. We find that hedge funds are more capable to generate price jumps than any other group, including sell-side analysts and buy-side participants from mutual funds and other buy-side institutions. The pair-wise differences are all positive and statistically significant at the 1% level. Our results related to adjusted trading volume are very similar. Overall, our results suggest that there exists a big dispersion within buy-side participants in information production and information complementarity. Clearly, hedge fund participants, relative to other buy-side participants, have the strongest ability to move prices and trigger trading activities.

In addition to supporting evidence for Prediction 1, we also observe the following interesting patterns from results reported in Table 4. First, consistent with Matsumoto et al. (2011), we find that both managers' presentations and Q&As between managers and call participants contain incremental information. The independent variable, *Manager's Presentation*, has positive and statistically significant coefficients in all regressions reported in Table 4. Matsumoto et al. (2011) suggest that Q&A sessions have greater information content than managers' presentation session. Our results do not support this notion. We argue that the result in Matsumoto et al. (2011) might be driven by the fact that Q&A sessions are on average longer than managers' presentations. Second, we observe different patterns of price jumps and trading volumes at the market open and the market close. At the market open, both the likelihood of price jump and adjusted trading volume increase significantly, reflecting that investors incorporate overnight information into stock prices at the market open. At the market close, we only observe a significant increase in trading volume. The change in the likelihood of price jump is insignificant based on the Lee and Mykland (2007) jump measure, and slightly negative (and marginally significant) based on the 1% cut-off jump measure. This is consistent with the explanation that many day traders would like to close their positions by the end of the day to avoid risk exposure to overnight information arrivals. Third, our results in Column (2) of Panels A and B suggest that time slots associated with managers' presentations and mutual fund participation are more likely to experience positive returns. This result is consistent with economic incentives of managers, who are more willing to disclose good news than bad news, and mutual funds, who usually do not benefit from negative news by creating short positions.

[Insert Table 5 Here]

One thing we have not examined above is whether buy-side (sell-side) participation is associated with negative and positive price jumps in a different manner. In Table 5, we investigate this issue based on multinomial logit regressions. We partition all observations based on the jump detection technique in Lee and Mykland (2007) into three subgroups: a subsample with negative price jumps, a subsample with positive price jumps, and a subsample with no price jumps. The subsample with no price jumps is the base group in our multinomial logit regressions. Results in Panel A suggest that both buy-side and sell-side participations in earnings conference calls are likely to trigger an increase in the probability of positive and negative price jumps. We test the difference between the impact of buy-side (sell-side) participation on the likelihoods of positive prices jumps and the impact on the likelihood of negative jumps. We find insignificant results. Results from this test suggest that, before we decompose buy-side participants into subgroups, buy-side participation and sell-side participation have symmetric effects on the likelihood of positive and negative price jumps.

In Panel B, we partition buy-side participants into three subgroups. We observe two striking patterns. First, time slots associated with hedge fund participation is more likely to experience negative price jumps than positive price jumps. Second, time slots associated with mutual fund participation is more likely to experience positive price jumps than negative price jumps. This result implies that buy-side institutions might specialize in producing different types of information conditional on their trading strategies and economic incentives. Specifically, hedge funds, who typically carry out a long-short strategy, are more sensitive to negative information than other buy-side institutions; at the same time, mutual funds, who typically carry out a long-and-hold strategy, are more sensitive to positive information than other buy-side institutions.

Overall, we find very supportive evidence for Prediction 1 that time slots associated with buy-side participation have a higher likelihood of price jumps and a higher adjusted trading volume, irrespective to whether we compare them with time slots outside earnings conference calls, time slots associated with sell-side participation, or time slots participated by mutual funds or other buy-side institutions. While we find that buy-side participation and sell-side participation are also related to a significant increase in within-slot return volatility, we do not find that buy-side participation has a stronger effect on within-slot return volatility than sell-side participation.

4.3 Prediction 2: Price Drift

Prediction 2 focuses on the relationship between buy-side participation and the post-conference-call price drift. We do not require synchronized transcripts and audios for all earnings conference calls to test Prediction 2. Therefore, our sample for this test includes all earnings conference calls within 48 hours after quarterly earnings announcements between 2003 and 2013.

Our test specification is very similar to that in DellaVigna and Pollet (2009). The dependent variable, *CAR [3, 20]*, is the cumulative abnormal returns based on the market model in a period from 3 trading days to 20 trading days after the earnings announcement. We group earnings conference calls in each quarter into five groups according to the earnings announcement effect, measured by *CAR [-2, 2]* (i.e., the cumulative abnormal returns based on the market model in a period from 2 trading days before to 2 trading days after the earnings announcement). *Top (Bottom)* is a dummy variable that is equal to 1 if the earnings announcement effect is ranked in top (bottom) 20 percentile within the quarter. *Buy Side* is a dummy variable that is equal to 1 if there is at least one buy-side analyst in the earnings conference call after the earnings announcement. While we partition buy side participants into three subgroups, *Buy Side - Hedge Fund*, *Buy Side - Mutual Fund*, and *Buy Side - Others* are defined similarly as *Buy Side*.

[Insert Table 6 Here]

Results of empirical tests for Prediction 2 are reported in Table 6. In Column (1), we observe that firms in the top (bottom) quintile based on earnings announcement effect are likely to experience positive (negative) price drifts in the testing period [3,20], 3 trading days to 20 trading days after the earnings announcement. This is a classic result of post earnings announcement drift (PEAD). While we interact the Top and Bottom dummies with Buy Side, we find that the interaction action term *Top*×*Buy Side* has a positive coefficient and *Bottom*×*Buy Side* has a negative coefficient, suggesting that, with buy-side participation of earnings conference calls, the magnitude of PEAD effect increases. However, in Column (1), none of these two coefficients is statistically significant.

In Column (2), we create dummy variables separately for three subgroups of buy-side participants. The coefficient of *Top*×*Buy Side - Hedge Fund* is 0.006 and the coefficient of *Bottom*×*Buy Side - Hedge Fund* is -0.007. Both coefficients are statistically significant at the 1% level. Relative to the unconditional effect represented by the coefficient of *Top* (i.e., 0.008), the coefficient of *Top*×*Buy Side - Hedge Fund* suggests that the magnitude of PEAD effect for firms within the top 20 percentile based on earnings announcement effect increases by 75% when buy-side participants raise questions in earnings conference calls. One can make a similar interpretation based on the coefficient of *Bottom*×*Buy Side - Hedge Fund*. On the other hand, the interaction term between *Top (Bottom)* and dummy variables for mutual fund participants (other buy-side participants) is statistically insignificant.

Overall, we find supportive evidence for Prediction 2 that buy-side participation is likely to associate with an increased magnitude in price drift after earnings conference calls. Once again, we find a big variation across different types of buy-side institutions and this effect is mainly driven by hedge fund participation. Our results suggest that private information held by hedge funds might be more "orthogonal" and "complementary" to information held by other investors, relative to information held by mutual fund participants and other buy-side participants.

5 Conclusion

We study the production and diffusion of diverse information in financial markets under a unique setting: Q&A sessions of earnings conference calls. In the setting, participants with diverse information (including corporate managers, sell-side analysts, and buy-side institutions) intensively interact with each other. With the features of underreaction and information complementarity, our model predicts that: 1) buy-side participation can trigger a larger price jump, a higher trading volume, and a higher return volatility than sell-side participation; 2) buy-side participation can generate a stronger price drift relative to the situation where buy-side participation is absent.

Taking advantage of high-frequency trading data with synchronized transcripts and audios of earnings conference calls, we establish the causal link between the information contained in participants' questions and the price/volume reactions. Consistent with the first prediction, we find that buy-side participation have a higher likelihood of experiencing price jumps and abnormal trading volumes. Furthermore, we test and confirm our second prediction that there is a stronger price drift after earnings announcement if the earnings conference calls are participated by hedge fund participants. Overall, our study contributes to the understanding of the information production, diffusion, and interaction in financial markets.

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Table 1: Summary Statistics of Analyst Participation in Earnings Conference Calls

Our sample includes trading days of 2216 earnings conference calls of U.S. listed companies from Q1 2012 to Q1 2013, where 1) the Q&A sessions of earnings conference calls are held during the trading hours; and 2) the audio files and the exact starting time of earnings conference calls are available from earningscast.com. Means of all variables reported in the table are corresponding to a 3-minute slot in trading hours (i.e., 9:30-16:00). Definitions of these variables are provided in Appendix I.

	Buy Side			Sell Side
	Hedge Funds	Mutual Funds	Others	Sell Side
% in All Participants	0.0372	0.0173	1.69%	91.52%
Duration of Q&As (Seconds)	216.148	266.765	241.391	216.396
Sequence	0.755	0.778	0.771	0.548
Num Words in Questions	180.581	213.142	185.588	167.582
Num Questions	4.508	5.413	4.412	4.297
Num Managers in Replies	1.713	1.826	1.664	1.856
Num Words in Managers' Replies	366.653	454.544	417.299	390.749
Total Number of Calls in the Sample			2216	
Avg Number of Analysts in One Call			7.309	

Table 2: Analyst Participation in Earnings Conference Calls: Buy Side vs. Sell Side

Our sample includes trading days of 2216 earnings conference calls of U.S. listed companies from Q1 2012 to Q1 2013, where 1) the Q&A sessions of earnings conference calls are held during the trading hours; and 2) the audio files and the exact starting time of earnings conference calls are available from earningscast.com. The dataset for the test reported in this table is organized at the analyst level, i.e., one observation captures one analystfis questions and the replies of these questions from managers. The definitions of dependent variables and independent variables are provided in Appendix I. In Panel A, the result is based on the comparison between buy-side and sell-side analysts. In Panel B, we classify buy side analysts into types according to their affiliations. In all specifications reported, we incorporate the call fixed effects. The standard errors, reported in parentheses, have been clustered at the call level. The superscripts ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Buy Side vs. Sell Side

	(1)	(2)	(3)
VARIABLES	Sequence	Num Words	Num Words in Reply
Buy Side	0.270***	14.996***	-27.665***
	(0.010)	(4.574)	(7.650)
Num Words			1.331***
			(0.028)
Sequence		-41.664***	-52.018***
		(2.605)	(5.815)
Call Fixed Effect	Yes	Yes	Yes
SE Clustered (Call Level)	Yes	Yes	Yes
Observations	16,197	16,197	16,197
R-squared	0.073	0.302	0.591

Panel B: Buy Side by Types

	(1)	(2)	(3)
VARIABLES	Sequence	Num Words in Questions	Num Words in Replies
Buy Side - Hedge Fund	0.241***	6.432	-35.765***
	(0.013)	(5.925)	(9.820)
Buy Side - Mutual Fund	0.256***	32.708***	9.88
	(0.016)	(9.891)	(14.872)
Buy Side - Other	0.294***	7.55	-41.248**
	(0.017)	(9.465)	(16.873)
Num Words			1.328***
			(0.028)
Sequence		-41.008***	-51.846***
		(2.609)	(5.824)
Call Fixed Effect	Yes	Yes	Yes
SE Clustered (Call Level)	Yes	Yes	Yes
Observations	16,197	16,197	16,197
R-squared	0.073	0.303	0.591
Difference			
Hedge Fund - Mutual Fund	-0.015	-26.276**	-45.645***
(t-stat)	(-0.72)	(-2.24)	(-2.57)
Hedge Fund - Other	-0.053**	-1.118	5.483
(t-stat)	(-2.56)	(-0.10)	(0.28)

Table 3: Summary Statistics for Trading Slots

Our sample includes trading days of 2216 earnings conference calls of U.S. listed companies from Q1 2012 to Q1 2013, where 1) the Q&A sessions of earnings conference calls are held during the trading hours; and 2) the audio files and the exact starting time of earnings conference calls are available from earningscast.com. Means of all variables reported in the table are corresponding to a 3-minute slot in trading hours (i.e., 9:30-16:00). Detailed definitions of these variables are provided in Appendix I.

	Buy Side			Sell Side
	Hedge Funds	Mutual Funds	Others	
% in Q&A Slots	5.21%	2.94%	2.51%	93.61%
% in Buy-side Participated Slots	52.43%	29.60%	25.28%	—
ABS(Ret) (%)	0.283	0.216	0.167	0.247
Ret (%)	-0.012	0.03	-0.024	-0.002
Jump (L&M)	0.125	0.091	0.045	0.04
Jump - 1% cut off	0.07	0.041	0.027	0.038
Adj. Vol	3.656	3.473	1.86	2.306
Log(1+Ret^2)	1.442	1.218	0.871	1.359
Log(1+STD)	4.694	4.203	3.525	5.616
Total Trading Slots (including pre- and post-conference call slots)	288,080			
Total Trading Slots in Manager's Presentation	17,405			
Total Trading Slots in Q&As	22,130			

Table 4: Q&As in Earnings Conference Call and Trading Activities during Q&As

Our sample includes trading days of 2216 earnings conference calls of U.S. listed companies from Q1 2012 to Q1 2013, where 1) the Q&A sessions of earnings conference calls are held during the trading hours; and 2) the audio files and the exact starting time of earnings conference calls are available from earningscast.com. All variables are corresponding to a 3-minute slot in trading hours (i.e., 9:30-16:00). Detailed definitions of dependent variables and independent variables are provided in Appendix I. Standard errors, shown in the parentheses, are clustered at the conference call level. The superscripts ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Buy Side vs. Sell Side

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	OLS	Logit	LPM	Logit	LPM	OLS	OLS	OLS
VARIABLES			Jump	Jump	Jump	Jump		Log	Log
	|Ret|	Ret	(LM)	(LM)	1% Cutoff	1% Cutoff	Adj. Vol	(1+Ret^2)	(1+STD)
Manager's Presentation	0.069***	0.007*	0.604***	0.019***	0.718***	0.023***	0.842***	0.325***	0.404***
	(0.004)	(0.004)	(0.048)	(0.002)	(0.047)	(0.002)	(0.093)	(0.015)	(0.024)
Q&A: Buy Side	0.046***	0.002	1.437***	0.065***	0.762***	0.018***	1.509***	0.204***	0.131**
	(0.010)	(0.012)	(0.081)	(0.007)	(0.117)	(0.005)	(0.329)	(0.037)	(0.064)
[Marginal Effect]			[0.039]		[0.020]				
Q&A: Sell Side	0.056***	-0.003	0.306***	0.012***	0.349***	0.012***	0.705***	0.254***	0.294***
	(0.005)	(0.005)	(0.050)	(0.002)	(0.053)	(0.002)	(0.078)	(0.015)	(0.021)
[Marginal Effect]			[0.008]		[0.009]				
Market Open	1.270***	-0.021	3.684***	0.445***	3.286***	0.345***	4.906***	2.551***	2.883***
	(0.030)	(0.035)	(0.038)	(0.006)	(0.037)	(0.006)	(0.232)	(0.033)	(0.041)
Market Close	0.020***	0.002	0.036	0.001	-0.169*	-0.003*	6.536***	0.167***	1.116***
	(0.004)	(0.004)	(0.094)	(0.002)	(0.100)	(0.002)	(0.171)	(0.018)	(0.034)
Call Fixed Effect	Yes	Yes	No	Yes	No	Yes	Yes	Yes	Yes
SE Clustered (Call Level)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	288,080	288,080	288,080	288,080	288,080	288,080	288,080	288,080	288,080
R-squared	0.191	0.008	0.163	0.156	0.122	0.138	0.079	0.22	0.38
Difference									
Buy Side - Sell side	-0.011	0.005	—	0.053***	—	0.006	0.804**	-0.05	-0.163**
(t-stat)	(-0.88)	(0.37)	—	(7.66)	—	(0.99)	(2.42)	(-1.23)	(-2.44)

Panel B: Buy Side Decomposition based on Types

VARIABLES	(1) OLS |Ret|	(2) OLS Ret	(3) Logit Jump (LM)	(4) LPM Jump (LM)	(5) Logit Jump 1% Cutoff	(6) LPM Jump 1% Cutoff	(7) OLS Adj. Vol	(8) OLS Log (1+Ret^2)	(9) OLS Log (1+STD)
Manager's Presentation	0.069***	0.007*	0.602***	0.019***	0.717***	0.023***	0.842***	0.325***	0.404***
	(0.004)	(0.004)	(0.048)	(0.002)	(0.047)	(0.002)	(0.093)	(0.015)	(0.024)
Q&A: Buy Side - Hedge Fund	0.077***	-0.013	1.597***	0.088***	1.046***	0.034***	1.799***	0.317***	0.237**
	(0.015)	(0.017)	(0.102)	(0.010)	(0.144)	(0.008)	(0.373)	(0.056)	(0.095)
[Marginal Effect]			[0.043]		[0.027]				
Q&A: Buy Side - Mutual Fund	0.01	0.039**	0.982***	0.043***	0.277	0.005	1.356	0.124**	-0.004
	(0.015)	(0.018)	(0.151)	(0.011)	(0.226)	(0.008)	(0.833)	(0.063)	(0.122)
[Marginal Effect]			[0.026]		[0.007]				
Q&A: Buy Side - Other	-0.008	-0.015	0.28	0.003	-0.063	-0.01	0.215	-0.059	-0.046
	(0.019)	(0.025)	(0.222)	(0.009)	(0.279)	(0.007)	(0.634)	(0.053)	(0.095)
[Marginal Effect]			[0.008]		[-0.002]				
Q&A: Sell Side	0.056***	-0.003	0.318***	0.012***	0.351***	0.012***	0.709***	0.254***	0.294***
	(0.005)	(0.005)	(0.050)	(0.002)	(0.053)	(0.002)	(0.078)	(0.015)	(0.021)
[Marginal Effect]			[0.009]		[0.009]				
Market Open	1.270***	-0.021	3.682***	0.445***	3.285***	0.345***	4.906***	2.551***	2.883***
	(0.030)	(0.035)	(0.038)	(0.006)	(0.037)	(0.006)	(0.232)	(0.033)	(0.041)
Market Close	0.020***	0.001	0.034	0.001	-0.170*	-0.003*	6.535***	0.167***	1.116***
	(0.004)	(0.004)	(0.094)	(0.002)	(0.100)	(0.002)	(0.171)	(0.018)	(0.034)
Call Fixed Effect	Yes	Yes	No	Yes	No	Yes	Yes	Yes	Yes
SE Clustered (Call Level)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	288,080	288,080	288,080	288,080	288,080	288,080	288,080	288,080	288,080
R-squared	0.191	0.008	0.163	0.156	0.122	0.138	0.079	0.22	0.38
Difference									
Hedge Fund - Mutual Fund	0.067***	-0.052**	—	0.045***	—	0.029**	0.443	0.193**	0.241
(t-stat)	(3.19)	(-2.17)	—	(3.00)	—	(2.42)	(0.47)	(2.25)	(1.52)
Hedge Fund - Other	0.085***	0.002	—	0.085***	—	0.044***	1.584*	0.376***	0.283**
(t-stat)	(3.42)	(0.05)	—	(5.89)	—	(3.90)	(1.92)	(4.70)	(2.00)
Hedge Fund - Sell Side	0.021**	-0.01	—	0.076***	—	0.021**	1.090***	0.063	-0.057
(t-stat)	(2.33)	(-0.60)	—	(7.45)	—	(2.46)	(2.86)	(1.08)	(-0.60)

Table 5: Analyst Participations and Price Jumps during Q&As: Evidence based on Multinomial Logistic Regression

Our sample includes trading days of 2216 earnings conference calls of U.S. listed companies from Q1 2012 to Q1 2013, where 1) the Q&A sessions of earnings conference calls are held during the trading hours; and 2) the audio files and the exact starting time of earnings conference calls are available from earningscast.com. All variables are corresponding to a 3-minute slot in trading hours (i.e., 9:30-16:00). The definitions of dependent variables and independent variables are provided in Appendix I. Standard errors, shown in the parentheses, are clustered at the conference call level. The superscripts ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Buy Side vs. Sell Side

	Positive Jumps	Negative Jumps
Manager's Presentation	0.609***	0.599***
	(0.061)	(0.060)
Q&A: Buy Side	1.406***	1.477***
	(0.114)	(0.105)
[RRR]	[4.081]	[4.380]
Q&A: Sell Side	0.350***	0.260***
	(0.061)	(0.068)
[RRR]	[1.418]	[1.297]
Market Open	3.673***	3.695***
	(0.043)	(0.044)
Market Close	-0.051	0.117
	(0.126)	(0.124)
SE Clustered (Call Level)	Yes	Yes
Observations	288,080	
Pseudo R-squared	0.141	

Panel B: Buy Side Decomposition based on Types

	Positive Jumps	Negative Jumps
Manager's Presentation	0.747***	0.687***
	(0.060)	(0.058)
Q&A: Buy Side - Hedge Fund	0.949***	1.134***
	(0.215)	(0.163)
[RRR]	[2.582]	[3.109]
Q&A: Buy Side - Mutual Fund	0.603**	-0.165
	(0.276)	(0.345)
[RRR]	[1.828]	[0.848]
Q&A: Buy Side - Other	-0.445	0.202
	(0.454)	(0.319)
[RRR]	[0.640]	[1.224]
Q&A: Sell Side	0.348***	0.354***
	(0.065)	(0.070)
[RRR]	[1.416]	[1.425]
Market Open	3.323***	3.247***
	(0.044)	(0.044)
Market Close	-0.253*	-0.095
	(0.141)	(0.130)
SE Clustered (Call Level)	Yes	Yes
Observations	288,080	
Pseudo R-squared	0.141	

Table 6: Buy-Side Participation and Post Earnings Announcement Drift

Our sample includes all earnings conference calls within 48 hours after quarterly earnings announcement between 2003 and 2013. The dependent variable, CAR[3, 20], the cumulative abnormal returns in a period from 3 trading days to 20 trading days after the earnings announcement. Top (Bottom) is a dummy variable that is equal to 1 if the earnings announcement effect (measured by CAR [-2,2]) is ranked in top (bottom) 20 percentile within the quarter. Buy Side is a dummy variable that is equal to 1 if there is at least one buy-side analyst in the earnings conference call after the earnings announcement. Buy Side: Hedge Fund, Buy Side: Mutual Fund, and Buy Side: Others are defined similarly. We have included year-quarter fixed effects in both specifications. Standard errors, shown in the parentheses, are clustered at the firm level. The superscripts ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) CAR [3, 20]	(2) CAR [3, 20]
Buy Side	-0.001	
	(0.001)	
Buy Side - Hedge Fund		-0.002*
		(0.001)
Buy Side - Mutual Fund		0.002
		(0.002)
Buy Side - Others		0.001
		(0.002)
Top	0.007***	0.008***
	(0.002)	(0.002)
Top × *Buy Side*	0.004	
	(0.002)	
Top × *Buy Side - Hedge Fund*		0.006**
		(0.003)
Top × *Buy Side - Mutual Fund*		-0.002
		(0.003)
Top × *Buy Side - Others*		-0.002
		(0.004)
Bottom	-0.008***	-0.007***
	(0.002)	(0.002)
Bottom × Buy Side	-0.004	
	(0.003)	
Bottom × Buy Side - Hedge Fund		-0.006**
		(0.003)
Bottom × Buy Side - Mutual Fund		-0.002
		(0.003)
Bottom × Buy Side - Others		-0.003
		(0.004)
Year-Quarter Fixed Effects	Yes	Yes
SE (Firm)	Yes	Yes
Observations	65,084	65,084
R-squared	0.024	0.024

Appendix I: Variable Definitions

Panel A: Analyst-Level Variables

Variables	Definition
Duration of Q&As (Seconds)	Duration (seconds) of one analyst's conversation with managers, including the time raising questions and the time receiving replies;
Sequence	The order of one analyst's Q&As scaled by total participants in the earnings conference call (i.e., smaller Sequence means earlier questions);
Num Words in Questions	Number of words in one analyst's all questions in the earnings conference call;
Num Questions	Number of questions one analyst asks in the earnings conference call;
Num Managers in Replies	Number of managers involved in replying one analyst's questions in the earnings conference call;
Num Words in Managers' Replies	Number of words in managers' reply to one analyst's questions;
Buy Side	Dummy variable that is equal to one if the analyst is affiliated with a buy-side institution, and zero otherwise;
Buy Side - Hedge Fund	Dummy variable that is equal to one if the analyst is affiliated with a hedge fund, and zero otherwise;
Buy Side - PE & VC	Dummy variable that is equal to one if the analyst is affiliated with a private equity or a venture capital, and zero otherwise;
Buy Side - Mutual Fund	Dummy variable that is equal to one if the analyst is affiliated with a mutual fund, and zero otherwise;
Buy Side - Others	Dummy variable that is equal to one if the analyst is affiliated with a buy-side institution that is not a hedge fund, private equity, venture capital or mutual fund;
Sell Side	Dummy variable that is equal to one if the analyst is affiliated with a sell-side institution.

Panel B: Time-Slot-Level Variables

Variables	Definition
ABS(Ret) (%)	Absolute return in the slot;
Ret (%)	Raw return in the slot;
Jump (L&M)	Dummy variable that is equal to one if there is a price jump defined in Lee and Mykland (2007), and zero otherwise;
Jump - 1% cut off	Dummy variable that is equal to one if there is a price jump defined by 1% cut off (positive or negative), and zero otherwise;
Adj. Vol	Dollar trading volume of the slot scaled by the average dollar trading volume for the previous one month;
AIM	Amihud Illiquidity Measure is defined as the absolute value of stock returns multiplied by 1,000,000, scaled by the dollar trading volume in the slot;
STD based on thirty-second-slots (%)	Standard deviation of stock returns based on third-second-slots within each three-minute slot;
Manager's Presentation	Dummy variable that is equal to one if managers are carrying out presentations in this slot, and zero otherwise;
Q&A: Buy Side	Dummy variable that is equal to one if a buy-side analyst is doing Q&As in this slot, and zero otherwise;
Q&A: Buy Side - Hedge Fund	Dummy variable that is equal to one if a buy-side analyst affiliated with a hedge fund is doing Q&As in this slot, and zero otherwise;
Q&A: Buy Side - Mutual Fund	Dummy variable that is equal to one if a buy-side analyst affiliated with a mutual fund is doing Q&As in this slot, and zero otherwise;
Q&A: Buy Side - Others	Dummy variable that is equal to one if a buy-side analyst that is not affiliated with a hedge fund or a mutual fund is doing Q&As in this slot, and zero otherwise;
Q&A: Sell Side	Dummy variable that is equal to one if a sell-side analyst is doing Q&As in this slot, and zero otherwise;
Market Open	Dummy variable that is equal to one if this slot belongs to the first three slots after the market opens;
Market Close	Dummy variable that is equal to one if this slot belongs to the last three slots before the market closes.

Appendix II: Sample Constructions

Number of Transcripts of Conference Calls between January 2012 - March 2013 from Reuters StreetEvent		13,584
Minus	Number of Calls that were not held during trading hours	-5,949
= Total Number of Calls that were held during trading hours		=7,635
Minus	Number of Calls where audios are not available from Earningscasts.com	-5,389
= Total Number of trading-hour Calls whose audios are available from Earningscasts.com		=2,246
Minus	Number of Audios with Synchronization Errors (e.g., due to missing sentences in transcripts)	-30
Number of Trading-hour Calls with Synchronized Audios from Earningscasts.com between January 2012 - March 2013		=2,216

Appendix III: Sample Comparison

	(1)	(2)	(3)	(3)-(1)	(3)-(2)
	All	Calls in Trading Hours	Synchronized Sample		
Total Assets (Mil)	12,123.94	11,922.24	11,792.251	-331.689	-129.989
Book Leverage	0.221	0.259	0.246	0.025*	-0.014
ROA	0.093	0.108	0.122	0.029**	0.014*
Book-to-Market	0.6	0.668	0.681	0.081***	0.014
Aanalyst Coverage	9.506	8.697	9.085	-0.421	0.388
Total Call Participants	7.179	7.002	7.309	0.13	0.307
Num of Calls	13,584	7,635	2,216		

Appendix IV: Analysts associated with more than 3 price Jumps in our sample

Panel A: Positive Jumps

Surname	First Name	Num Jumps	Sell Side	Buy Side	Affiliation	Buy Side Types
BAKER	JIMMY	4	1	0	B. RILEY & CO.	
THOMPSON	KATHRYN	4	1	0	THOMPSON RESEARCH GROUP	
COPPOLA	NICK	3	1	0	THOMPSON RESEARCH GROUP	
HAIMES	BARRY	3	0	1	SAGE ASSET MANAGEMENT	HEDGE FUND
HALL	ROD	3	1	0	JPMORGAN SECURITIES INC.	
LAPPIN	JOAN	3	0	1	GRAMERCY CAPITAL	HEDGE FUND
MACOSKO	GREGORY	3	0	1	LORD ABBETT	MUTUAL FUND
MATTHEWS	JEFFREY	3	0	1	RAM PARTNERS	HEDGE FUND
MILLER	MARK	3	1	0	WILLIAM BLAIR & COMPANY	
PEARLSTEIN	SAM	3	1	0	WELLS FARGO SECURITIES, LLC	
SCHMITZ	BILL	3	1	0	DEUTSCHE BANK	
TULLIS	RICHARD	3	1	0	CAPITAL ONE SOUTHCOAST, INC.	
WALTHAUSEN	JOHN	3	0	1	WALTHAUSEN & COMPANY	MUTUAL FUND
WEINSWIG	DEBORAH	3	1	0	CITIGROUP	
BAKER	JIMMY	4	1	0	B. RILEY & CO.	

Panel B: Negative Jumps

Surname	First Name	Num Jumps	Sell Side	Buy Side	Affiliation	Buy Side Types
SOMMER	TOBEY	4	1	0	SUNTRUST ROBINSON HUMPHREY	
DUIGNAN	ANN	3	1	0	JPMORGAN CHASE & CO.	
EVANS	BRAD	3	0	1	HEARTLAND ADVISORS	MUTUAL FUND
FLEISHMAN	STEVE	3	1	0	BOFA MERRILL LYNCH	
GORDON	GREG	3	1	0	ISI GROUP	
GRAHAM	SCOTT	3	1	0	JEFFERIES & COMPANY	
GREENDALE	COREY	3	1	0	FIRST ANALYSIS SECURITIES	
KOSOWSKY	ROBERT	3	1	0	SIDOTI & COMPANY	
LIU	JINMING	3	1	0	ARDOUR CAPITAL INVESTMENTS	
LUCAS	BARRY	3	1	0	GABELLI & COMPANY	
OBUS	NELSON	3	0	1	WYNNEFIELD CAPITAL, INC	HEDGE FUND
RUSSO	BRIAN	3	1	0	LADENBURG THALMANN & COMPANY INC.	
SCHWARTZ	STEVE	3	1	0	FIRST ANALYSIS SECURITIES	
URDAN	TRACE	3	1	0	WELLS FARGO SECURITIES, LLC	