The Information Role of Earnings Conference Calls: How Earnings Calls Alter Demand for Quarterly Reports

Wenyao Hu
Lally School of Management
Rensselaer Polytechnic Institute
huw3@rpi.edu

August 2020

The Information Role of Earnings Conference Call: How Earnings Calls Alter Demand for Quarterly Reports

August 2020

Abstract

This paper investigates how qualitative and quantitative information in earnings calls change the information acquisition for mandated filings via EDGAR. Using a large sample of earnings conference call from 2007 to 2017, I find that both qualitative and quantitative information in earnings call impede the following information acquisition activities through EDGAR. To establish a causal relation, I use the weather condition on earnings call date as the instrument for information released during earnings calls. After implementing 2SLS regression, I confirm that more information within earnings calls leads to a reduction in information acquisition through EDGAR. I also examine this information acquisition activity on market reaction and find high information acquisition via EDGAR decrease short-term market reaction and delay in-time analyst forecast revisions. I also confirm the increase in information acquisition via EDGAR is due to the processing costs difference between mandated filings and earnings calls by separating my original sample according to the level of processing difficulties of firm's earnings calls.

Keywords: Conference Calls; Corporate Disclosure; Information Acquisition; EDGAR

1. Introduction

The corporate information environment is largely explained by three main factors: voluntary disclosures, mandatory disclosures, and information intermediaries. While many studies investigate the impact of each factor in shaping the information environment, most studies focus on a single information source and ignore the interdependencies and complementarities among sources (Beyer et al., 2010; Blankespoor, deHaan and Marinovic, 2020). In response to the demand for further analysis into the interplay of these factors, I study the interrelationship between earnings conference calls and mandated financial reports in the eyes of investors. Earnings calls are meetings held by publicly traded firms in conjunction with earning press releases, where company executives provide information to investors. Previous research shows that investors, even non-current holders, consume earnings conference calls as their source of information (Heinrichs, Park and Soltes, 2020). Nevertheless, to the best of my knowledge, none of this previous research looks at the link between consumption of earnings calls and mandated filings.

In this study I examine whether the information content within earnings calls promotes or impedes the consumption of mandated Securities and Exchange Commission (SEC) filings. Previous research suggests that the market tends to process information in earnings press releases or earnings conference calls more efficiently than the information in 10-Q and 10-K filings (Stice 1991; Louis et al. 2008; Levi 2008). Literature also argues that information within earnings calls is easier for investors to understand and integrate into their decision-making model (Bushee et al., 2003; Einhorn,2005; Ball et al., 2012). More information made available through earnings conference call can hinder the consumption of mandated financial filings due to processing costs.

My primary focus in this research is the both quantitative information and qualitative information in earnings conference calls. Previous research demonstrates that market participants response not only to quantitative information, but also to qualitative information, such as tone of earnings-related disclosures. (Frankel et al., 1999; Brown et al., 2004; Kimbrough, 2005; Davis et al, 2012; Price et al., 2012). To measure the quantitative information in earnings calls, I use the similar method as Zhou (2018) to count the numbers of numerical terms in each conference calls. Similar to previous research, I use linguistic tone, which is the percentage different between positive words and negative words in earnings calls, as the measurement for qualitative information For acquisition activities for mandated filings, I use the web traffic data from SEC's Electronic Data Gathering, Analysis and Retrieval (EDGAR) online database containing detailed information acquisition activities for each request to the EDGAR server.

EDGAR web traffic data has several distinguishing features in terms of content and format, compared to other information acquisition measurements such as Google search and Bloomberg attention. For EDGAR web traffic, it captures the direct acquisition activities of specific filings for each firm through the unique Central Index Key (CIK) and accession numbers associated with each filling. Other measurements, such as Google search, can only provide an ambiguity terms (e.g., WIFI can be Boingo Wireless Inc or wireless networking technologies) and a relative search intensity[1]. In my research, I start by constructing the information acquisition activities through EDGAR as the overall views for accounting related filings, such as 10-Q and 10-K, in the three days after earnings conference call.

To examine the impact of information within earnings calls on investor's information acquisition through EDGAR, I first collect all available earnings calls transcripts in Capital IQ

[1] Google only provide the relative search intensity from 0-100, but not the real search numbers.

and combine with EDGAR web traffic data and relevant accounting and analyst information, which accounts for a total 51,855 firm-quarter observations between 2007 to 2017. Using firm fixed effects to control for unobserved, time-invariant differences across firms in information usage in earnings calls and information acquisition activities through EDGAR, and year fixed effects to control for common time trends, I find that earnings calls with more information, in terms of both quantitative and qualitative information, have lower information acquisition activities through EDGAR after the calls. The results are consistent with the idea that investors prefer to process the low-processing cost disclosures such as earnings calls to complex mandated financial filings which is less readable. More readable disclosure increase the investors' confidence that they can rely on that disclosure (Rennekamp,2012). The above result holds when I: (i) control for firm-year fixed effect; (ii) control for days of week fixed effects; (iii) use propensity-score matched pairs; (iv) control for earnings call dates fixed effect, (v) use only executive-specific information usage.

However, there may be alternative explanations for these results. For instance, executive may strategically choose the type and amount of information be released through different disclosure channels. By introducing an instrumental variable, the weather condition on the earnings call date, to estimate the impact of quantitative information on information acquisition activities, I attempt to establish a causal relationship between these information within earnings call and the acquisition activities via EDGAR. Francis, Hu and Shohfi (2020) document that executives are affected by the weather conditions during earnings conference call date. Executives speak less positively and use less quantitative information when weather condition is bad. Furthermore, the weather conditions on the conference call date in headquarter location do not have a direct impact on the investors' acquisition of EDGAR activities. After implementing

2SLS regression, I confirm that more quantitative and qualitative information leads to a reduction in the acquisition of information through EDGAR after the earnings calls. To confirm my explanation that these negative relations are due to investor's preference to low processing cost disclosure, I further sperate my original sample according to the difficulty in processing the conference call. I find consistent result that result is less significant when: i) the readability of earnings conference call is low; ii) firm is small; iii) few analysts are following the company.

Next, I examine whether the information acquisition via EDGAR affects the reaction from investors, both in terms of market reaction and analysts' reaction. To do so, I first test whether market response, which is measured by the cumulative abnormal returns (CARs) within three days of earnings call date, is influenced by the information acquisition activities from investor. As mandated filings are too complex and cause information overload to investors (Paredes, 2003; Guay et al., 2016), I expect the market to react negatively to the number of information acquisition activities through EDGAR. The results support my expectation. Controlling for net tone, quantitative information in the call, I find that the total numbers of information acquisition via EDGAR decreases the market reaction. A one standard deviation change in the numbers of information acquisitions results market reaction reduction by 0.23% which translates into an average reduction of $35 million market value of the firm.

I also examine the impact on analyst forecast revision. Following Bochkay, Hales and Chava (2020), I study the impact of information acquisition activity through EDGAR on analyst forecast revisions made within 10 days following the earnings call. If more information acquisition activities through EDGAR slow down analysis, I expect fewer analyst forecast revisions, especially fewer upward forecast revision, to be issued within 10 days of the call. As such, I show that both the total number of revisions and the upward revisions decreased when more information acquisition activities are undertaken in EDGAR after the earnings call.

Collectively, these findings show strong evidence that the information released during earnings calls decreases demand for information from EDGAR. This decreased information acquisition activities via EDGAR causes a positive market reaction to earnings calls and induces more in-time analyst forecast revisions.

My paper highlights the importance of earnings calls as compared with mandated financial filings. In December 2018, the SEC requested comments on earnings releases and quarterly reports. One of their concerns is whether investors rely on information from quarterly reports. My research shows that when more information is available on earnings calls, investors pay less attention to financial information in quarterly reports. Quarterly filings may be viewed as secondary sources of information to investors if they have not received enough information from earnings calls.

My study's contribution is fourfold. First, my analysis illuminates a deeper understanding of the demand for firm information. Previous research documents the demand for mandatory disclosures and voluntary disclosure separately (Drake, Roulstone and Thornock, 2016; Heinrichs, Park and Soltes, 2020). None of the previous literature, to the best of my knowledge, shows the interrelation of demand between these two disclosures. Using detailed information acquisition activity through EDGAR, I show that the information acquisition activity for mandated filings is negatively related to the information within voluntary disclosure. By exploring the consumption of mandated filings and information in earnings calls, this research provides a better understanding of investor preferences in the processing of information.

Second, this study contributes to the literature on voluntary disclosure by documenting how the acquisition of information for mandated filings influences the immediate reaction of investors. Gibbons, Iliev and Kalodimos (2020) indicate that the acquisition of information through EDGAR reduces future forecast errors. However, they do not account for the processing cost of financial filings. In this research, I document that both short-term market reactions and analysts' in-time forecasts are declining if they rely on financial information from EDGAR.

Third, my study sheds further light on what determines the information acquisition activity through EDGAR. Drake, Roulstone and Thornock (2015) indicate that EDGAR activities are related to corporate events and the stock market performance. My analysis shows that information in earnings conference call also affect the information acquisition activities through EDGAR.

Finally, my paper also adds to the current debate on the usefulness of quarterly reports. The SEC has raised the question as to whether investors rely on the information within quarterly reports. My results suggest that investors prefer disclosures with low information processing costs such as earnings conference call and use financial filings as a secondary source of information. Specifically, if there is not enough information on earnings calls, such as quantitative information, investors will search for information in quarterly filings.

The remainder of the paper is organized as follows. Section 2 reviews prior work and develops hypotheses. Section 3 describes my data and discusses my empirical approach. Section 4 presents my empirical findings. Section 5 provides additional analysis and the robustness check. Finally, section 6 concludes.

2. Literature Review and Hypothesis Development

2.1 Firms' Information Environment

Corporate disclosure is critical to the functioning of an efficient capital market. Firms can release information to the public through voluntary and mandatory disclosures. Mandated financial filings disclose information helpful to valuing the firm, including periodic financial reports, ad-hoc publications, or other regulatory filings. In addition, some firms engage in voluntary communication, such as press releases, conference calls, management forecast and other corporate reports.

The most common mandatory disclosures are 10-Ks containing performance information for the past fiscal year and 10-Qs which has the results for each of the first three quarters of the fiscal year. In other words, the company files three 10-Qs and one 10-Ks electronically to the SEC through its EDGAR system each year. Corresponding with these mandated financial filings, firm may also engage in voluntary communication activities, such as earnings press releases or conference calls, to help investors better interpret mandatory disclosures.

Previous research demonstrates that managers have an incentive to mitigate the complexity of mandated filings by issuing voluntary disclosures. Bushee et al. (2003) find that firms with more complex transactions are more likely to open their conference calls to public. Similarly, Guay et al. (2016) illustrate that firms with less readable financial reports will provide more management forecasts to mitigate the negative impact of the complexity of financial statements. More recently, Chen et al. (2018) find that firms engaged in more tax evasion activities will provide more management guidance.

Under the mosaic theory of financial analyses, information mandated by regulators is combined with other publicly available information to arrive at an investment decision. Many of the previously theoretical and empirical studies on mandatory or voluntary disclosure just focused on one specific type of disclosure (e.g. Kim & Verreccia, 1991; Dechow et al., 2010; Bosch and Lee, 1994; Sarkar and De Jong, 2006). With this focus, they ignore the fact that different disclosure channels interact with each other.

The nature of the relationship between mandatory and voluntary disclosure has been studied by Gigler and Hemmer (1998), Einhorn (2005), Ball et al. (2012), as well as Li and Yang (2016). All these studies conclude that these two types of disclosures are mutually complementary. For instance, Gigler and Hemmer (1998) show how mandatory reporting complements voluntary disclosures of private information, by playing a confirmatory role in an agency setting where voluntary disclosures are motivated by the desire to achieve efficient contracting. However, this prior research only stands at manager's view to investigate the relation between voluntary disclosure and mandated financial filings. None of the previous literature, to the best of my knowledge, looks at the interdependence between these two factors in investors' perspectives.

2.2 Effect of Investor Information Demand

Investor's information choices are constrained by three types of disclosure processing costs: awareness costs, acquisition costs, and integration costs (Blankespoor, DeHaan and Marinovic, 2020). Each cost plays an important role in investors' information acquisition through firms' disclosures. Complexity is a key factor in determining processing costs, especially integration costs. You and Zhang (2009) demonstrate that 10-K filings with more complex language experience greater drift than less complex filings. Similarly, Huang et al. (2018) show that investors rely more heavily on analyst interpretation when firms' conference calls include more uncertain language.

A major concern for mandatory disclosures is whether investors fully understand and utilize the information contained in the disclosure. This concern arises from the fact that mandatory disclosure rules are too complex and cause information overload for investors (Paredes, 2003; Guay et al., 2016). Previous research suggests that the market tends to process information in earnings press releases or earnings conference calls more efficiently than the information in 10-Q and 10-K filings (e.g., Stice 1991; Louis et al. 2008; Levi 2008). Similarly, Beyer et al. (2010) show that among the set of disclosure events for which they test relative importance, management guidance and earnings announcements are the most price-relevant, while SEC filings are the least relevant.

2.3 Information Insides Earnings Conference Calls

The use of conference calls as a medium for voluntary disclosure has grown enormously over the last decade. Indeed, quarterly conference calls after earnings releases are now more or less routine (Bowen, Davis, and Matsumoto,2002). Earlier research examines those factors that influence a firm's decision to host a conference call (e.g., Tasker, 1998; Frankel, Johnson, and Skinner, 1999), whether calls are informative for investors (Frankel, Johnson, and Skinner, 1999), and how earnings conference calls affect analysts' forecasts (Bowen, Davis, and Matsumoto, 2002). Collectively, the evidence suggests that conference calls play an important role in resolving the information asymmetry problem between managers and outside investors.

A firm frequently holds an earnings conference call within a day of issuing an earnings announcement. Calls typically include a presentation by the firm's management followed by a question and answer session with invited financial market participants. The conference call literature, though small relative to the voluminous earnings announcement research, yields interesting insights into the use of and reaction to calls. A conference call may provide information about a firm incremental to that disclosed in its earnings release for several reasons. According to practitioner surveys (National Investor Relations Institute 2014), the presentation section of a conference call often provides supplemental disclosure from several key executives. In addition, the conference call contains non-scripted disclosure driven by the questions of financial market participants such as sell-side analysts. Conference calls may also offer soft information, such as the firm's choice and order of speakers, the tone and vocal cues of management, and the presence and attitudes of other participants. (Loughran and McDonald, 2016; Mayew and Venkatachalam, 2012)

As these calls are usually held in conjunction with the publication of financial reports, the question arises as to whether company management uses conference calls to merely repeat the content of a financial reports or uses a call to deliver new value-relevant information. Previous research finds that conference calls are incrementally informative and are used to provide additional details and elaborations (Matsumoto et al., 2011). The provision of new value-relevant information should thus result in unexpected trading activities and price developments during the conference call time window (Holthausen and Verrecchia, 1990), because investors are expected to process this new information quickly and react accordingly by adjusting their shareholdings.

To my knowledge, research is silent on the connection between these two disclosures, leaving an important gap in the understanding of the interplay between conference calls and financial reports. With this study, I take a step toward filling this void as well as addressing the noted dearth of research on the potential mechanisms facilitating information choice from investor between these two disclosure channels.

2.4 Literature on EDGAR Web Traffic Data

As my work utilizes the web traffic information from the SEC EDGAR system, my paper is related to a few recent articles that use this data to explore the different issue in both finance and accounting. One of the first paper that looks into this data is done by Drake, Roulstone and Thornock (2015). They show that EDGAR activity is positively related to corporate events and previous performance. They also point out that EDGAR behavior is related to, but distinct from, other investor interest measures, such as trading volume and Google search volume. By using the same dataset, Loughran and McDonald (2017) draw a similar conclusion that the number of requests is related to form type and timing. However, they also argue that the average request for a firm's annual report is 28.4 times greater by investors immediately following a 10-K filling, even after removing the robotic requests.

Previous research also demonstrates the usefulness of investors' information acquisition activities for financial filings in EDGAR system. Drake, Roulstone, and Thornock (2016) indicate that requests for historic reports during the fiscal year are positively associated with financial reporting complexity and that requests around earnings announcements are positively associated with accounting discretion and negative earnings shocks. Drake, Roulstone, and Thornock (2020) conclude that information acquisition of accounting reports by EDGAR users is, on average, predictive of future firm performance.

More recently, researchers have shifted the focus to another dimension of data that EDGAR log file can provide: the masked IP addresses which can give partial identification for the viewer. One of the first papers to do this is Lee et al. (2015). They apply a unique algorithm to the SEC web traffic data to identify the neighborhood search done by the same individual and find these firms are fundamentally similar in various dimensions.

Nowadays, scholars tried to unmask the IP address to get the detail information for each viewer. Bozanic et al. (2017) identify the IP addresses belong to the IRS and find IRS search behavior is related to the level of the public disclosure requirement. Chen et al. (2020) examine the search behavior of 13-F for mutual fund and find that mutual fund managers follow trades of some specific company's insider, and this set of the company is highly persistent. More recent work is done by Dyer (2018). In his paper, he mainly studies whether local institutional investor uses public information to generate an information advantage to make a profit by trading local stocks.

2.5 Hypothesis Development and Empirical Prediction

In this section I develop the formal hypotheses that inform my two research objectives. The first set of hypotheses are related to the relation between information acquisition activities through EDGAR and information insides earnings calls. My hypothesis is that investors' acquisition activities via EDGAR are determined, at least in part, by the information insides earnings conference calls.

As the objective of an earnings conference call is to reduce the complexity of or clarify mandated filings, the information inside an earnings calls should be easier for investors to understand and integrate into their decision-making models. (Bushee et al., 2003; Einhorn,2005; Ball et al., 2012 and Chen et al., 2018). Previous research suggests that the market tends to process information in earnings press releases or earnings conference calls more efficiently than the information in 10-Q and 10-K filings (e.g., Stice 1991; Louis et al. 2008; Levi 2008). By using an experiment, Rennekamp(2012) confirms that more readable disclosure increase the investors' confidence that they can rely on that disclosure. As the conference calls are incrementally informative over the mandated financial filings with lower processing cost and more readable (Frankel et al. 1999; Bushee et al. 2003; Matsumoto et al. 2011), investors would prefer conference call and view mandated fillings as secondary source of information. Investors will process the mandated documents only if easier processing disclosure, which is earnings call in my setting, didn't provide enough information. I thus hypothesize that:

Hypothesis 1: Quantitative information inside earnings conference calls is negatively correlated with information acquisition activities in EDGAR by investors following earnings calls.

The second set of hypotheses relates to market responses to the information acquisition activities in EDGAR. Compared to the information insides earnings conference calls, information insides financial reports is more complex and needs more effort to be processed. Existing research shows that mandated filings are too complex and cause information overload for investors (Paredes, 2003; Guay et al., 2016). Previous research also suggests that the market tends to process information in earnings press releases or earnings conference calls more efficiently than the information in 10-Q and 10-K filings (e.g., Stice 1991; Louis et al. 2008; Levi 2008). If investors relied more on inefficient financial reports, due to their complexity, they will need more time to process financial reports. This long processing time will cause a negative shock to short-term market reaction. Thus, I hypothesize that:

Hypothesis 2: High information acquisition activity in EDGAR after earnings conference calls is associated with more negative short-term market reaction.

A second way to test whether market participants respond to information acquisition activities via EDGAR is to examine its impact on analyst behavior. A number of studies show that analysts' processing of information from voluntary disclosures is more efficient than mandated filings. Lehavy, et al. (2011) show that higher Fog index in 10-Ks is associated with greater dispersion, lower accuracy, and greater overall uncertainty in analyst earnings forecasts. Using earnings press releases, Bozanic and Thevenot (2015) find that higher readability in the form of shorter sentences, textual similarity, and lexical diversity are associated with decreases in analysts' uncertainty. Loughran and McDonald (2014) propose that the file size of the 10-K document submitted to the SEC is a better proxy for readability. They document that greater 10-K file size is also associated with larger analyst forecast dispersion and higher forecast errors.

As a result, earnings conference calls contain more condensed and easier to understand language than quarterly filings. If analysts relied more on mandatory filings, I expect a slower revision of the analyst 's forecast as they would need more time to process the information. Based on this argument, I hypothesize:

Hypothesis 3: High information acquisition activity in EDGAR after earnings conference call is associated with slower analyst forecast revision.

3. Data and Research Design

Data for the main analysis comes from several sources. My initial sample consists of all earnings conference call transcripts within Capital IQ from 2007 through 2017. I merge all of the available firms with web traffic data from EDGAR, which is available from the SEC's division of economic and risk analysis[2]. After combining with available accounting information and analyst coverage information from Compustat and Institutional Brokers' Estimate System (I/B/E/S), the final sample consists of 51,855 firm-quarter level observations. To mitigate the effect of outliers, I winsorize all continuous variables at the 1st and 99th percentiles.

[2] The web server log file can be downloaded from https://www.sec.gov/dera/data/edgar-log-file-data-set.html

3.1 Measuring Information Acquisition Activities via EDGAR

My primary source of data on investor's information acquisition is the Electronic Data Gathering, Analysis, and Retrieval system (EDGAR) log file. The EDGAR log data contains all requests for EDGAR filings through SEC.gov which spans from January 2003 to June 2017. Log files provide the IP address, filling accessed, the CIK of the public company and the date of access for each request. The raw EDGAR log files contain records for each download request. In order to observe the investor's use of financial information, I need to remove all downloads made by robots. I 'm following Ryan's (2017) procedure to clean up the robot 's views. Ryans (2017) mainly compares the different methods used to screen robot requests and argues that his method is superior relative to other approaches (Drake et al., 2015 and Loughran and McDonald, 2016). Details for the human-view construction process from the EDGAR log file dataset are presented in Appendix I. Following the application of the procedure, the initial EDGAR sample containing more than 47 billion records has been reduced to approximately 1.1 billion records. To summarize the EDGAR log data at the CIK level, I aggregate the cleaned data at the CIK-filling day level.

To calculate the information acquisition activities related to accounting information after the earnings conference calls, I restrict my focus to requests for the periodic filings[3] (such as 10-K or 10-Q). Drake et al. (2015) argue that the requests for periodic accounting reports are increasing during the announcement of annual earnings. In order to isolate the influence of information inside the earnings call for information acquisition activities through EDGAR, I focus on short-term acquisition activities. In my main regression, I use the acquisition activities in the three

[3] I include all forms of periodic financial reports: 10-K, 10-K/A, 10-KT,10KT/A,10-Q.10-Q/A,10-QT

days after the earnings calls, but my results are consistent if I change my measurement to 1 day to 5 days after the earnings conference calls. Thus, I calculate the following measure as a proxy of the information acquisition activities after the earnings conference calls:

$$IA[1,3] = Ln(\ Periodic\ fillings\ request\ over\ days\ [1,3]\ relative\ to\ call\ date + 1)$$

As shown in the above equation, I use the natural logarithm of the number of EDGAR requests for periodic financial reports between days 1 and days 3 after an earnings conference call.

In my robustness check, I also separate the institutional investors' request for filings from the other requests. I follow the same method as the previous literature by identifying the IP address of the institutional investor (Drake et al, 2016; Dyer, 2017). Specifically, I identify the views of the institutional investor using the ARIN WHOIS database, which contains a list of the names of the organizations and the IP addresses they own. Next, I matched the names in the ARIN WHOIS file with the names in SEC 13-F files[4]. After finding IP addresses owned by an institutional investor, I check the IP address of each request and assign the relevant IP address to each institutional investor[5]. After this process, I have successfully identified 1,496 institutional investors. I use the same method as above by calculating requests for accounting information request by an institutional investor three days after the earnings calls and constructing a variable called IAInst[1,3].

The summary statistics related to information acquisition around earnings calls are presented in Table 1. On average, information requests occur for roughly 103 times in the 3 days following earnings conference calls. The mean count of institutional investors' information acquisition is

[4] I use a name match program in Python called "fuzzy-wuzzy" which will return a matching score for each matched name. I only keep the score larger than 95 (the highest score is 100).
[5] As the last three digits are missing in EDGAR log file, I assigned an IP address to the firm which owns the largest share of IP addresses in that IP range.

around 1 time. It is similar to previous research, as an institutional investor may have other resources to obtain information such as data vendors.

3.2 Measuring Information Insides Earnings Conference Calls

For the measurement of quantitative information in earnings conference calls, I follow Zhou (2018) and count the number of numeric phrases in each transcript and exclude whole numbers from 1,950 to 2,050 to avoid including mention of years in the transcripts. The specific formula is as follows:

$$\%QI = \frac{Total\ Numbers}{Total\ Words + Total\ Numbers} \times 100$$

where Total Numbers is calculated using the method above and Total Words is the total count of all words in each transcript. The average for *%QI* is 2.5% percent which is similar to Zhou (2018).

Other than the quantitative information, I also construct the qualitative information measurement for all earnings calls. In line with previous finance and accounting literature, using text sentiment to represent qualitative information in earnings conference calls (e.g., Huang, Teoh and Zhang , 2014; Davis et al., 2015), I rely on finance-oriented Loughran and McDonald (2011) dictionaries to calculate the net tone as a percentage of positive words minus the percentage of negative words. More formally,

$$Net\ Tone\ = \frac{Positive\ Words - Negative\ Words}{Total} Words \times 100$$

The mean of Net Tone is 0.71% which is similar to previous studies examining earnings conference call content (Davis et al., 2015).

3.3 Potential Endogeneity and Instrumental Variable Approach

To identify the impact of quantitative information within earnings calls on investor's information acquisition through mandated filings, the information in earnings calls should be exogenous to investors' choice to access financial reports. However, potential endogeneity concerns arise. For example, an omitted factor such as firm characteristics could affect both quantitative information and investor's information acquisition decision.

I use one instrumental variable to capture exogenous variations in quantitative information during earnings calls. My instrument for both qualitative and quantitative information are weather conditions during the earnings conference call date around the firm's headquarter. I construct this instrument based on Francis, Hu and Shohfi (2020) using weather data from the Integrated Surface Database (ISD), which is available from the National Oceanic and Atmospheric Administration (NOAA).[6]. The ISD database contains hourly weather observations such as cloud cover, temperature, sea pressure, etc. from 1901 to 2017. As the focus of my study is U.S. firms, I collect the data from all active weather stations located in the U.S.[7] The ISD database also provides the latitude and longitude coordinates of each weather station which makes the calculation of distance between each weather station and firm headquarters possible.

I follow previous literature by taking the average of hourly cloud cover data around the headquarters during daytime which is from 6 am to 6 pm (Dehann, Masden, and Piotroski, 2017; Francis, Hu and Shohfi, 2020). To overcome the seasonality of cloud cover in each city, I adjust the cloud data seasonally by following the approach used by Hirshleifer and Shumway (2003).

[6] ftp://ftp.ncdc.noaa.gov/pub/data/noaa

[7] I define a weather station as active if the station is operational during my sample period and provides the cloud cover measurement. The average number of concurrently active stations in my study is approximately 3600.

3.4 The Regression Model and The Ordinary Least Squares Specification

To study the effects of information insides earnings calls on mandated filling's acquisition, I use the following linear regression model:

$$IA[1,3]_{i,t} = \alpha_1 QI_{i,t} + X_{i,t}\beta + v_i + W_T + \epsilon_{i,t} \qquad (1)$$

$IA[1,3]_{i,t}$ represent the financial information acquisition activities through EDGAR within 3 days after the earnings conference call for firm i and quarter t. $QI_{i,t}$ is the percentage of quantitative information ($\%QI$) or the linguistic tone (*Net Tone*) insides an earnings conference call at firm i and quarter t. The regression analysis focuses on the coefficient for $QI_{i,t}$, α_1. $X_{i,t}$ is a vector of controls variables. v_i stands for the firm fixed effects, which absorb firm-specific and time invariant components in investors' decisions to acquire financial information through EDGAR and alleviate time series correlation in EDGAR's information acquisition due to firm fixed effects (Drake et al, 2015). W_T stands for year fixed effects, used to control for common time trends in information acquisition through EDGAR across all industries and firms. $\epsilon_{i,t}$ is a random error terms that is assumed to be possibly heteroskedastic and correlated over time. I cluster standard errors at the firm level.

To estimate the market reaction to the information acquisition activities through EDGAR, I use the similar OLS method as above with different specification:

$$Y_{i,t} = \alpha_1 IA[1,3]_{i,t} + X_{i,t}\beta + v_i + W_T + \epsilon_{i,t} \qquad (2)$$

$Y_{i,t}$ is the market reaction variables, such as the cumulative abnormal return (CAR) or mean analyst forecast revisions. The definition for $IA[1,3]_{i,t}$ is similar to equation (1) as the information acquisition activities in 3 days after the earnings calls. I also include controls ($X_{i,t}$), firm fixed effects (v_i) and year fixed effects (W_T) as equation (1) to isolate the effect of information acquisition on market reactions.

3.5 Control Variables

I follow previous literature on the selection of control variables (see, for example, Huang, Teoh and Zhang , 2014; Davis et al . , 2015; Drake et al., 2015). I include two types of variables that are known to influence both market reactions and the acquisition of information through EDGAR. The first relates to firm status and financial performance in each quarter. I control for *Accruals* measured as accruals relative to total assets, market capitalization (*Ln(Size)*), *Book to Market ratio*, *Return on Assets* and *Negative Earnings* which is an indicator variable that equals one when the firm reports a negative earnings result in that quarter.

The second set of controls relates to pressure from outside stakeholders such as investors and analysts. The variables are *Surprise Earnings* measured as the difference between actual earnings and consensus analyst forecast divided by the standard deviation of analyst forecast, the number of analysts following the company in the conference call quarter (*Ln(Analysts)*), number of earnings estimates made by analysts during that quarter (*Ln(Revisions)*), and an indicator variable to distinguish whether the firm met earnings expectations in that quarter (*Meet Expectations*).

In addition, I also control for the linguistic tone of each earnings call. To do so, I rely on the Loughran and McDonald (2011) finance-oriented dictionaries to calculate net tone as a percentage of positive words minus the percentage of negative words in the earnings conference call.

Finally, I follow Chen et.al. (2018) by controlling for the time of day in which the conference call takes place. The authors point out that the tone of conference calls deteriorates markedly over the course of the day, to which they attribute to a decline in the energy level of executives. As a result, I create an indicator variable (*Afternoon*) to distinguish calls held before or after 12 noon.

In my sample, less than 40% of calls are made in the afternoon which is similar to that reported by Chen et al. (2018). Detailed definitions of all variables can be found in Appendix II.

3.6 Summary Statistics

Table 1 displays my sample summary statistics. The statistics of my explanatory variables are similar to those of previous research. The average profit surprise for a typical firm in my sample is 0.81. The average firm has a follow-up of 7,61 analysts with an average of 1,09 forecast revisions per analyst-quarter. My sample firms have an average log-transformed firm size of 7.50, which translates into $1.80 billion of assets, and an average book to market ratio of 0.55. In addition, 14.3% of the firms in my sample report a loss in a given quarter and 71.3% of the observations meet the consensus analyst earnings forecast.

[insert Table 1 here]

4. Empirical Result

4.1 Univariate Analysis

I begin my empirical analysis by providing univariate results of the relationship between the information insides earnings call and the request for financial information within the EDGAR system. Results are presented in Table 2 where I divided the original sample into two subsamples based on the median level of information in conference calls in each firm-quarter. Panel A of Table 2 shows that the difference between the download requests in earnings calls with more quantitative information and the ones with less quantitative information is around 23 times, which is equivalent to an increase of 25% and is statistically significant at the 1% level. This significant difference is also present in the case of subsamples that separate based on the level of qualitative information.

There is a 34% difference in the download activity between the different level of qualitative information within the earnings call subsamples.

[insert Table 2 here]

Results in Table 2 provide initial evidence that information inside earnings conference call maybe substituted for financial information insides financial filings, but other control variables are also different between firms with different levels of information insides earnings calls. Among the differences, firms with more quantitative (qualitative) information within earnings calls tend to be smaller, have a lower percentage of firms with negative earnings, have lower estimates of revisions, higher book to market ratios, and are more (less) likely to hold calls in the afternoon. Many of these differences are likely to affect requests for information through EDGAR. To control for these time-variant firm variables, I use a multivariate regression analysis to examine the relationship between quantitative information within earnings call and EDGAR download requests. I also use a propensity score matching method to mitigate difference in control variables in the latter part of this paper.

4.2 Information Requests and Quantitative Information Insides Earnings Calls

The results reported in Table 3 show both the effect of information inside the earnings calls on total financial information requests. I use three model specifications for the two types of information: quantitative and qualitative information. In column (1) and (2), I regress each type of information insides earnings calls on information requests activities and include firm and year fixed effects. In column (3), I add all of my control variables and two information measurement together. In the remaining column, I further restrict my sample to an interaction between firm and year fixed effect.

[insert Table 3 here]

The coefficients for both *%QI* and *Net Tone* are negative and statistically significant at the 1% level across all columns of Table 3, which are consistent with my first hypothesis. These results are not only statistically significant but also economically significant. One standard deviation change in %QI (*Net Tone*) decreases total information requests from EDGAR by 4% (3%) when I include control variables and fixed effects.

In addition, I document other firm characteristics that drive the information acquisition through EDGAR after the earnings calls. Specifically, the information acquisition activities are higher for firms with larger size, more analyst following, and more institutional ownership. On the other hand, firms with large book to market ratio and better profitability experiences less information acquisition through EDGAR.

4.3 Instrumental Variable Specification

In order to identify the causal effect of earnings calls' information on the acquisition of financial information, I estimate an instrumental variable (IV) regression using weather conditions during the earnings conference call. Francis, Hu and Shohfi (2020) demonstrate that weather conditions influence both qualitative and quantitative information released during earnings conference calls. Following their methodology, I estimate the 2SLS equations by using cloud cover information around the headquarters of each firm during the earnings call date as the instrument. The IV regressions are conducted in two stages. In the first stage, I regress *%QI* (*Net Tone*) on daily cloud cover, firm controls, and fixed effects. In the second stage, I estimate the regression model in Eq. (1) while replacing *%QI* (*Net Tone*) by the predicted value of %QI (*Net Tone*) from the first-stage regression. The regression results are summarized in Table 4.

[insert Table 4 here]

Panel A of Table 4 reports the first stage regression for weather condition on information within earnings calls. The results are consistent with previous research that bad weather will decrease both the numerical information and linguistic tone used by executives. The columns of Panel B in Table 4 show the IV estimates of the effects of qualitative and quantitative information within earnings calls on information acquisition via EDGAR. The estimated coefficients are negative and statistically significant. The results are consistent with the OLS results while supporting a causal interpretation of the impact of both qualitative and quantitative content with earnings calls on information acquisition activities via EDGAR. The effects are economically significant as well. A coefficient of -0.903 (-1.030) implies that a one standard deviation increase in quantitative (qualitative) information in earnings conference call for an average firm leads to a 63% (61%) increase in information acquisition through EDGAR. Noticeably, both estimates are much greater in magnitude than the estimates from the OLS models.

4.4 Propensity Score Matching

In this section, I seek to address a potential issue in my univariate analysis table that there may be significant differences in firm characteristics between firms holding earnings calls with different level of information. To overcome this concern, I adopt a propensity-score matching (PSM) method to construct a balanced sample between firms in different qualitative or quantitative information groups.

The first step of this PSM method is to construct the prediction model by using the indicator variable I constructed in Table 2 as the dependent variable, which is presented in Panel A of Table 5.

[insert Table 5 here]

Panel B of Table 5 shows summary statistics for my matched sample. I have matched, without replacement, 20,695 (19,019) firm-quarters observations with a corresponding control observation and the matching rate is approximately 80% for quantitative (qualitative) information matched sample. The matching result works well since differences between control variables in the treatment and control groups are not statistically significant.

I rerun my main regression analysis examining the relationship between information inside earnings call and information acquisition through EDGAR. All of these results are shown in Panel C of Table 6. These results are similar to those in Tables 3 and 4 which indicates that my results are not driven by any differences in firm characteristics for earnings conference calls with more or less quantitative information inside.

4.5 Channel Tests

As my story indicates these negative relations are due to investors' information processing costs, I further sperate my original sample according to the difficulty in processing the conference call as previous literature (Chambers and Penman, 1984; Bernard and Thomas, 1989; Hirshleifer et al., 2009 and Bochkay, Hales and Chava, 2020). I use firm size, analyst following, and readability index in earnings calls to test the moderating effect of information environment and processing costs on investors' information processing preference.

The amount of information available increase in firm size. Small firms tend to be less transparent and with less media coverage. Therefore the processing cost for earnings calls from small firms is larger than large firms. Similarly, analysts often issue analyst reports that combine different information outlets to give more digested information to investors. As a result , investors in low analyst follow-up firms need more efforts to evaluate the information in earnings calls which will increase chance to look at original financial filings. Finally, the degree of readability in earnings conference call is direct measurement for processing cost in earnings calls. If earnings calls are hard to read, investors may choose to find information in SEC reports.

Each quarter I separate firms into 2 groups based on their size, analyst following and fog index of earnings calls, and create three indicator variables for small size, low analyst following and high fog index of earnings calls based on the quartile of the variable. For instance, I will use the bottom (top) quarter of size and analyst following to create an indicator for small size and low analyst following (fog index of calls). Then, I interact these variables with my two information measurements in earnings calls, controlling for firm characteristics and fix effects. The result is showed in Table 6.

[insert Table 6]

Table 6 indicates that all my results reported in Table 3 are less significant for firms with high processing cost in earnings calls. This is consistent with my explanation that the decrease in information acquisition via EDGAR is due to the low processing cost within earnings calls.

4.6 Investor Reaction to Information Request from EDGAR

In this subsection, I examine whether the information acquisition though EDGAR affects the reactions from investors, both in terms of market reaction and analysts' reaction. To do so, I first test whether market reaction, which is measured by the cumulative abnormal returns (CARs) within three days after the earnings call, is influenced by the information acquisition activities from investor. Then I switch my focus to analysts, who are the important intermediaries to enhance firm information environment. I examine whether the efficiency of analyst forecast is changed by the information acquisition activities.

4.6.1 Stock Market Reaction

As mandated filings are too complex and cause information overload for investors (Paredes, 2003; Guay et al., 2016), I expect that the market will react negatively to the number of information acquisition activities through EDGAR. After implementing equation (2), the results are shown in column (1) of Table 7.

[insert Table 7]

The estimation results of equation (2) are shown in Table 6.The control variables are similar to those in Equation (1) except that I add *%QI* and *Net Tone* as an additional control here. The coefficient for information acquisition *IA[1,3]* is negative and statistically significant. In terms of economic significance, a one standard deviation increases in information acquisition information acquisition from institutional investor) decreases the market reaction by 0.226% which translates into a $35 million equity value reduction, on average, for sample firms. Taken together, these results provide strong support for the third hypothesis that increase in information acquisition through EDGAR will decrease the stock market reaction around the earnings conference calls.

4.6.2 Analyst Reaction

Another way to test whether market participants' information acquisition behavior change the market reaction is to examine the impact that such activity has on analyst behavior. While analysts likely have more accurate forecast when they use the information insides EDGAR (Gibbons, Iliev and Kalodimos, 2020), their tendency to issue an timely forecast revision may be lower if they need to process more time-consuming disclosure like quarterly reports or other mandated filings. Following Bochkay, Hales and Chava (2020), I study the impact of information acquisition activity through EDGAR on analyst forecast revisions made within 10 days following the earnings call.

I use two different measures to capture analysts' response to information acquisition via EDGAR. Controlling for underlying firm performance and other characteristics, I first examine how information acquisition through EDGAR influences the up revision of analyst forecast. I then test an association between the total number of analyst forecast revision and information acquisition activities. If analysts, similar to investors, revise their expectations based on the difficulties in information acquisition, I expect analyst revision activities to be negatively associated with information requests through EDGAR. The result is presented in last two columns of Table 7.

In Table 7, I find that information acquisition activity is strongly associated with all these two measures of analysts' revision activities in the 10-day window after the earnings call. For instance, when I use the total of forecast revision as the dependent variable, the coefficient estimates on *IA[1,3]* is -0.018. I observe similar results when I use only the number of up forecast revisions. The coefficient estimates on *IA[1,3]* for *Ln(Up Revision)* are -0.019. These results support my last hypothesis that more information acquisition activity via EDGAR decreases both analysts forecast revisions and up revisions.

5. Additional Analysis and Robustness Check

5.1 Manager's Specific Information Usage

My interpretation of the empirical findings is that information acquisition activities through EDGAR after earnings call are negatively related to information inside earnings calls. One of my identification strategies uses weather conditions which change the amount of qualitative and quantitative information within the earnings call. As noted by Francis, Hu and Shohfi (2020), weather-induced quantitative information usage is mainly driven by the pessimistic level change in manager's perception of company's future. If investor do not react to manager's specific number use, my identification strategy will not valid.

As a result, I apply the same method as described by Huang, Teoh, and Zhang (2014) by extracting both the specific number usage and linguistic tone of managers. They regress the net tone on firm fundamentals and use the residual to represent the manager's specific tone usage. By using both the net tone and %QI, I employ the similar procedure to generate the manager's specific information usage. Specifically, I first calculate the residuals from a regression identical to that of Column (2) in Table 3 but without textual sentiment measurement. I then use these residuals as an independent variable to replace the %QI in equation (1). The result is shown in Table 8.

[insert Table 8 here]

Panel B of Table 8 reports the coefficient for *Residual %QI and Residual Net Tone* are still negative (coefficient of -0.026 and -0.075) and highly significant (t-statistic of -3.300 and -8.339). Ceteris paribus, this result confirms the validity of my IV approach.

5.2 Information Acquisition Activities from Institutional Investor

Previous results view the investors as a single group. However, institutional investors may have better information processing ability and better information sources. However, Drake, Roulstone and Thornock (2016) mention that institutional investors are more likely to use filings directly from EDGAR as data providers are often delayed in displaying SEC filings on their platforms. Thus, I hypothesize that the information acquisition effect is similar to that of individual investors as institutional investors: To test this prediction, I construct a measurement for financial information acquisition only for institutional investor and rerun the equation (1) and (2) by replacing *IA[1,3]* with *IAInst[1,3]*. The result is reported in Table 9.

[insert Table 9 here]

The results in Table 9 are similar when I use the information acquisition activities from institutional investor only. These consistent results confirm the negative relation between information acquisition activity and information within earnings calls.

5.3 Other Qualitative Information Measurement in Earnings Calls

Another dimension to look at the qualitative information within earnings call is the linguistic extremity. Bochkay, Hales and Chava (2020) provide evidence that extreme language carries information beyond the traditional tone measurement. To construct an extreme language dictionary, they employed individuals from Amazon's Mechanical Turk service to evaluate a total of 23,355 words and phrase in earnings conference calls from -5 (extremely negative) to 5 (extremely positive). They measure the extreme language as the words and phrases with an absolute sore equal to 4 or 5. Following their approach, I download the dictionary from their website[8] and construct the same measurement for *SignedExtreme*, *SignedModerate*, *ExtrWordsInPositive* and *ExtrWordsInNegative* in my analysis:

$$SignedExtreme = \frac{Number\ of\ Words\ Rated\ as\ \text{"4" or "5"} - \text{Number of Words Rated as"-4" or "-5"}}{Number\ of\ All\ Words} \times 100$$

$$SignedModerate = \frac{Number\ of\ Words\ Rated\ as\ \text{"1", "2" or "3"} - \text{Number of Words Rated as "-1", "-2" or "-3"}}{Number\ of\ All\ Words} \times 100$$

$$ExtrWordsInPositive = \frac{Number\ of\ Words\ Rated\ as\ \text{"4" or "5"}}{Number\ of\ Words\ Rated\ as\ \text{1", "2" ,"3", "4" or "5"}} \times 100$$

$$ExtrWordsInNegative = \frac{Number\ of\ Words\ Rated\ as\ \text{"-4" or "-5"}}{Number\ of\ Words\ Rated\ as\ \text{"-1", "-2" ,"-3", "-4" or "-5"}} \times 100$$

The first two measurements – *SignedExtreme* and *SignedModerate*- are similar to traditional measures of tone but using the new dictionary constructed by Bochkay, Hales and Chava (2020).

---

[8] The extremity dictionary can be found at textart.us.

To isolate the effect of linguistic extremity, I also construct *ExtrWordsInPositive (ExtrWordsInNegative)* which is the percentage of extreme positive (negative) words in total positive (negative) words. The result is shown in Table 10.

[insert Table 10 here]

In the first two columns of Table 10, I find that both extreme language usage and moderate language usage are negatively associated with information acquisition activities via EDGAR. This is consistent with the idea that qualitative information matters for investor's information acquisition choice. As mentioned by Bochkay, Hales and Chava (2020), these measurements are a combination of tone and extremity. To separate these two concepts, they defined the extremity as the percentage of extreme words in terms of total sentiment words. Column (3) and (4) replace *SignedExtreme* and *SignedModerate* with *ExtrWordsInPositive and ExtrWordsInNegative* and run the same regression as before. The results show that investors do care about the linguistic extremity and react negative (positive) to positive (negative) extremity. Surprisingly, individual investors only care negative extremity but not positive extremity. This is also consistent with the idea that sophisticated investors are better skilled at interpreting soft information. (Blau, DeLisle and Price, 2015 and Kalay, 2015)

5.4 Timing of Earnings Calls

One endogeneity concern is that managers strategically adjust their disclosure choice based on the performance of their company. For instance, previous research demonstrates that managers tend to report bad earnings news on busy days (Hirshleifer et al., 2009; DeHaan et al., 2015 and Driskill et al., 2020). This strategy reduces attention and price reaction from investors. In addition, Niessner (2015) finds that managers release bad news on Fridays to reduce price responsiveness and implement insider trades. Earlier research also indicates that investors' preferences for leisure are stronger on Fridays, causing them to devote fewer resources to processing firms' disclosures (Patell & Wolfson, 1982 and Damodaran, 1989). To mitigate this concern, I add two fixed effects into my baseline regression in Table 3— the days of week fixed effect and call date fixed effect in Table 11.

[insert Table 11 here]

Column (1) and (2) of both Table 11 reports the baseline result with days of week fixed effect and the last two columns present the result for the regression with call date fixed effect. The coefficient for %QI is significant across all columns in Table 11. This consistent result indicates that my result is not driven by manager's endogenous timing selection or investors' processing ability.

6. Conclusion

This paper investigates the information insides earnings calls on following information acquisition activities via EDGAR. Specifically, I find that earnings conference calls with more information contents, both in terms of quantitative information and qualitative information, will decrease investors' information acquisition activities through EDGAR. My result suggests that investors are prefer to easy processing disclosure like earnings calls and only obtain mandated filings if earnings calls didn't provide sufficient information.

To mitigate the endogenous concerns in the relation between the information in earnings calls and information acquisition via EDGAR, I use the weather condition on earnings call date as the instrumental variable to establish a causal relation to the above two variables. Francis, Hu and Shohfi (2020) document that quantitative information usage by executives is affected by the weather condition on earnings conference call date. After implementing 2SLS regression, I confirm that more quantitative information lead to lower information acquisition activities through EDGAR after the earnings calls. This result holds when I: (i) control for firm-year fixed effect; (ii) control for days of week fixed effect; (iii) use propensity-score matched pairs; (iv) control for earnings call dates fixed effect, (v) use only executive-specific quantitative information usage.

I also examine the effects of information acquisition via EDGAR on the response from investor and show that high information acquisition through EDGAR can decrease short term market reaction and delay analyst forecast revisions. This decreasing in reactions from investors is due to the high processing cost to complex mandated filings.

Collectively, these findings show strong evidence that the quantitative information released during earnings calls impede information activities through EDGAR. This decreased information acquisition activities through EDGAR causes a positive market reaction to earnings calls and induces a more in-time analyst forecast revisions. One drawback for this paper is the limitation from EDGAR web traffic data. As the low overall requests indicate that it is unlikely to be most investors' primary source of disclosures. However, this is the only source that can track investors direct usage of financial disclosures.

References

Ball, R., Jayaraman, S., & Shivakumar, L. (2012). Audited financial reporting and voluntary disclosure as complements: A test of the confirmation hypothesis. *Journal of accounting and economics*, *53*(1-2), 136-166.

Beyer, A., Cohen, D. A., Lys, T. Z., & Walther, B. R. (2010). The financial reporting environment: Review of the recent literature. *Journal of accounting and economics*, *50*(2-3), 296-343.

Blankespoor, E., deHaan, E., & Marinovic, I. (2020). Disclosure processing costs, investors' information choice, and equity market outcomes: A review. *Journal of Accounting and Economics*.

Bochkay, K., Hales, J., & Chava, S. (2020). Hyperbole or reality? Investor response to extreme language in earnings conference calls. *The Accounting Review*, *95*(2), 31-60.

Bosch, J. C., & Lee, I. (1994). Wealth effects of Food and Drug Administration (FDA) decisions. *Managerial and Decision Economics*, *15*(6), 589-599.

Bowen, R. M., Davis, A. K., & Matsumoto, D. A. (2002). Do conference calls affect analysts' forecasts?. *The Accounting Review*, *77*(2), 285-316.

Bozanic, Z., & Thevenot, M. (2015). Qualitative disclosure and changes in Sell-Side financial analysts' information environment. *Contemporary Accounting Research*, *32*(4), 1595-1616.

Bozanic, Z., Hoopes, J. L., Thornock, J. R., & Williams, B. M. (2017). IRS attention. *Journal of Accounting Research*, *55*(1), 79-114.

Bushee, B. J., Matsumoto, D. A., & Miller, G. S. (2003). Open versus closed conference calls: the determinants and effects of broadening access to disclosure. *Journal of Accounting and Economics*, *34*(1-3), 149-180.

Chen, C. W., Hepfer, B. F., Quinn, P. J., & Wilson, R. J. (2018). The effect of tax-motivated income shifting on information asymmetry. *Review of Accounting Studies*, *23*(3), 958-1004.

Chen, H., Cohen, L., Gurun, U., Lou, D., & Malloy, C. (2020). IQ from IP: Simplifying search in portfolio choice. *Journal of Financial Economics*.

Chen, J., Demers, E., & Lev, B. (2018). Oh what a beautiful morning! Diurnal influences on executives and analysts: Evidence from conference calls. *Management Science*, *64*(12), 5899-5924.

Damodaran, A. (1989). The weekend effect in information releases: A study of earnings and dividend announcements. *The Review of Financial Studies*, *2*(4), 607-623.

Davis, A. K., Ge, W., Matsumoto, D., & Zhang, J. L. (2015). The effect of manager-specific optimism on the tone of earnings conference calls. *Review of Accounting Studies*, *20*(2), 639-673.

De Franco, G., Kothari, S. P., & Verdi, R. S. (2011). The benefits of financial statement comparability. *Journal of Accounting Research*, *49*(4), 895-931.

Dechow, P., Ge, W., & Schrand, C. (2010). Understanding earnings quality: A review of the proxies, their determinants and their consequences. *Journal of accounting and economics*, *50*(2-3), 344-401.

DeHaan, E., Shevlin, T., & Thornock, J. (2015). Market (in) attention and the strategic scheduling and timing of earnings announcements. *Journal of Accounting and Economics*, *60*(1), 36-55.

Dehaan, Ed, Joshua Madsen, and Joseph D. Piotroski, 2017, Do Weather-Induced Moods Affect the Processing of Earnings News?, *Journal of Accounting Research* 55, 509–550.

Drake, M. S., Johnson, B. A., Roulstone, D. T., & Thornock, J. R. (2020). Is there information content in information acquisition?. *The Accounting Review*, *95*(2), 113-139.

Drake, M. S., Roulstone, D. T., & Thornock, J. R. (2015). The determinants and consequences of information acquisition via EDGAR. *Contemporary Accounting Research*, *32*(3), 1128-1161.

Drake, M. S., Roulstone, D. T., & Thornock, J. R. (2016). The usefulness of historical accounting reports. *Journal of Accounting and Economics*, *61*(2-3), 448-464.

Driskill, M., Kirk, M. P., & Tucker, J. W. (2020). Concurrent Earnings Announcements and Analysts' Information Production. *The Accounting Review*, *95*(1), 165-189.

Dyer, T. (2018). Does public information acquisition level the playing field or widen the gap? An analysis of local and non-local investors.

Einhorn, E. (2005). The nature of the interaction between mandatory and voluntary disclosures. *Journal of Accounting Research*, *43*(4), 593-621.

Francis, B. B., Hu, W., & Shohfi, T. (2020, April). Does Executive Temperament Supersede Disclosure Content? Evidence from Weather Effects during Earnings Conference Calls. In *Evidence from Weather Effects during Earnings Conference Calls (April 20, 2020)*.

Frankel, R., Johnson, M., & Skinner, D. J. (1999). An empirical examination of conference calls as a voluntary disclosure medium. *Journal of Accounting Research*, *37*(1), 133-150.

Gibbons, B., Iliev, P., & Kalodimos, J. (2020). Analyst information acquisition via EDGAR. *Management Science*.

Gigler, F., & Hemmer, T. (1998). On the frequency, quality, and informational role of mandatory financial reports. *Journal of Accounting Research*, *36*, 117-147.

Guay, W., Samuels, D., & Taylor, D. (2016). Guiding through the fog: Financial statement complexity and voluntary disclosure. *Journal of Accounting and Economics*, *62*(2-3), 234-269.

Heinrichs, A., Park, J., & Soltes, E. F. (2019). Who Consumes Firm Disclosures? Evidence from Earnings Conference Calls. *The Accounting Review*, *94*(3), 205-231.

Hirshleifer, D., & Shumway, T. (2003). Good day sunshine: Stock returns and the weather. *The Journal of Finance*, *58*(3), 1009-1032.

Hirshleifer, D., Lim, S. S., & Teoh, S. H. (2009). Driven to distraction: Extraneous events and underreaction to earnings news. *The Journal of Finance*, *64*(5), 2289-2325.

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

Huang, A. H., Lehavy, R., Zang, A. Y., & Zheng, R. (2018). Analyst information discovery and interpretation roles: A topic modeling approach. *Management Science*, *64*(6), 2833-2855.

Huang, X., Teoh, S. H., & Zhang, Y. (2014). Tone management. *The Accounting Review*, *89*(3), 1083-1113.

Kim, O., & Verrecchia, R. E. (1991). Trading volume and price reactions to public announcements. *Journal of accounting research*, *29*(2), 302-321.

Lee, C. M., Ma, P., & Wang, C. C. (2015). Search-based peer firms: Aggregating investor perceptions through internet co-searches. *Journal of Financial Economics*, *116*(2), 410-431.

Lehavy, R., Li, F., & Merkley, K. (2011). The effect of annual report readability on analyst following and the properties of their earnings forecasts. *The Accounting Review*, *86*(3), 1087-1115.

Levi, S. (2008). Voluntary disclosure of accruals in earnings press releases and the pricing of accruals. *Review of Accounting Studies*, *13*(1), 1-21.

Li, X., & Yang, H. I. (2016). Mandatory financial reporting and voluntary disclosure: The effect of mandatory IFRS adoption on management forecasts. *The Accounting Review*, *91*(3), 933-953.

Liberti, J. M., & Petersen, M. A. (2019). Information: Hard and soft. *Review of Corporate Finance Studies*, *8*(1), 1-41.

Loughran, T., & McDonald, B. (2011). When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *The Journal of Finance*, *66*(1), 35-65.

Loughran, T., & McDonald, B. (2014). Measuring readability in financial disclosures. *The Journal of Finance*, *69*(4), 1643-1671.

Loughran, T., & McDonald, B. (2016). Textual analysis in accounting and finance: A survey. *Journal of Accounting Research*, *54*(4), 1187-1230.

Louis, H., Robinson, D., & Sbaraglia, A. (2008). An integrated analysis of the association between accrual disclosure and the abnormal accrual anomaly. *Review of Accounting Studies*, *13*(1), 23-54.

Matsumoto, D., Pronk, M., & Roelofsen, E. (2011). What makes conference calls useful? The information content of managers' presentations and analysts' discussion sessions. *The Accounting Review*, *86*(4), 1383-1414.

Mayew, W. J., & Venkatachalam, M. (2012). The power of voice: Managerial affective states and future firm performance. *The Journal of Finance*, *67*(1), 1-43.

Niessner, M. (2015). Strategic disclosure timing and insider trading. *Available at SSRN 2439040*.

Paredes, T. A. (2003). Blinded by the light: Information overload and its consequences for securities regulation. *Wash. ULQ*, *81*, 417.

Patell, J. M., & Wolfson, M. A. (1982). Good news, bad news, and the intraday timing of corporate disclosures. *Accounting review*, 509-527.

Rennekamp, K. (2012). Processing fluency and investors' reactions to disclosure readability. *Journal of Accounting Research*, *50*(5), 1319-1354.

Ryans, J. (2017). Using the EDGAR log file data set. *Available at SSRN 2913612*.

Sarkar, S. K., & de Jong, P. J. (2006). Market response to FDA announcements. *The Quarterly Review of Economics and Finance*, *46*(4), 586-597.

Stice, J. D. (1991). Using financial and market information to identify pre-engagement factors associated with lawsuits against auditors. *Accounting Review*, 516-533.

Tasker, S. C. (1998). Bridging the information gap: Quarterly conference calls as a medium for voluntary disclosure. *Review of Accounting Studies*, *3*(1-2), 137-167.

You, H., & Zhang, X. J. (2009). Financial reporting complexity and investor underreaction to 10-K information. *Review of Accounting studies*, *14*(4), 559-586.

Zhou, D. (2018). Do Numbers Speak Louder Than Words?. *Available at SSRN 2898595*.

Table 1

Descriptive Statistics

This table presents summary statistics for all variables in my sample. The sample period is 2006-2017. Detailed definitions for each variable are provided in Appendix II. All continuous variables are winsorized at 1% and 99% level.

VARIABLES	N	Mean	Std Dev	Q1	Median	Q3
Ln(Size)	51,855	7.494	1.891	6.132	7.467	8.714
Book to Market	51,855	0.554	0.446	0.257	0.461	0.753
Return on Asset	51,855	0.004	0.040	0.001	0.009	0.020
Net Tone	51,855	0.710	0.600	0.316	0.712	1.107
% QI	51,855	2.508	0.783	1.951	2.422	2.968
Afternoon	51,855	0.356	0.479	0.000	0.000	1.000
Firm Risk	51,855	0.136	0.443	-0.126	0.093	0.323
Accrual	51,855	-0.029	0.066	-0.050	-0.019	0.001
Ln(Analyst)	51,855	2.029	0.848	1.609	2.079	2.708
Ln(Revision)	51,855	0.090	0.433	0.000	0.074	0.336
Surprise Earnings	51,855	0.805	3.040	-0.327	0.212	1.745
Meet Expectation	51,855	0.713	0.452	0.000	1.000	1.000
Negative Earnings	51,855	0.143	0.350	0.000	0.000	0.000
Total Downloads	51,855	102.600	685.700	24.000	53.000	109.000
Total Inst Downloads	51,855	1.064	3.652	0.000	0.000	1.000
Total Revision	37,527	3.998	3.845	1.000	3.000	5.000
Up Revision	37,527	2.281	3.115	0.000	1.000	3.000
IA[1,3]	51,855	3.943	1.134	3.219	3.989	4.700
IAInst[1,3]	51,855	0.382	0.630	0.000	0.000	0.693
Large Info	51,855	0.497	0.500	0.000	0.000	1.000
Ln(Up Revision)	37,527	0.891	0.733	0.000	0.693	1.386
Ln(Total Revision)	37,527	1.401	0.609	0.693	1.386	1.792
% Inst Own	51,855	0.720	0.274	0.596	0.793	0.914
CARs(0,+3)	51,855	0.181	8.264	-3.789	0.098	4.209

Table 2

Univariate Analysis

This table shows univariate analyses for major variables in my sample. I separate the sample into two groups according to the median of the percentage of information in earnings calls each quarter. More Quantitative (Qualitative) Info equals one when percentage of quantitative (qualitative) information in earnings calls is larger than the median level in my sample in a given quarter. Detailed definitions for each variable are provided in Appendix II. Significance level: *** p < 0:01, ** p < 0:05, * p < 0:1.

Panel A: Quantitative Information Separation

	More Quantitative Info			Less Quantitative Info				
	N	Mean	Std Dev	N	Mean	Std Dev	Difference	T-statistics
Dependent Variable								
Total Downloads	25,760	91.070	221.200	26,095	113.900	941.200	-22.830***	-3.813
IA[1,3]	25,760	3.839	1.121	26,095	4.045	1.137	-0.206***	-20.775
Control Variables								
Ln(Size)	25,760	7.377	1.837	26,095	7.609	1.936	-0.232***	-13.999
Book to Market	25,760	0.585	0.462	26,095	0.523	0.428	0.062***	15.848
Return on Asset	25,760	0.005	0.038	26,095	0.004	0.042	0.001*	1.698
Afternoon	25,760	0.383	0.486	26,095	0.330	0.470	0.053***	12.621
Firm Risk	25,760	0.147	0.445	26,095	0.125	0.440	0.022***	5.660
Accrual	25,760	-0.030	0.066	26,095	-0.028	0.066	-0.002***	-4.134
Ln(Analyst)	25,760	1.916	0.847	26,095	2.141	0.834	-0.225***	-30.477
Ln(Revision)	25,760	0.050	0.460	26,095	0.129	0.401	-0.079***	-20.756
Surprise Earnings	25,760	0.875	3.137	26,095	0.736	2.941	0.139***	5.204
Meet Expectation	25,760	0.716	0.451	26,095	0.711	0.453	0.005	1.259
Negative Earnings	25,760	0.134	0.341	26,095	0.152	0.359	-0.018***	-5.854
% Inst Own	25,760	0.705	0.281	26,095	0.734	0.265	-0.029***	-12.087

Panel B: Qualitative Information Separation

	More Qualitative Info			Less Qualitative Info				
	N	Mean	Std Dev	N	Mean	Std Dev	Difference	T-statistics
Dependent Variable								
Total Downloads	25,222	87.031	135.4	26,633	117.323	947.521	-30.270***	-5.158
IA[1,3]	25,222	3.881	1.112	26,633	4.002	1.151	-0.121***	-12.175
Control Variables								
Ln(Size)	25,222	7.452	1.879	26,633	7.538	1.902	-0.086***	5.177
Book to Market	25,222	0.618	0.496	26,633	0.493	0.384	0.125***	31.967
Return on Asset	25,222	0.002	0.044	26,633	0.008	0.035	-0.006***	-21.839
Afternoon	25,222	0.338	0.473	26,633	0.373	0.484	-0.035***	-8.327
Firm Risk	25,222	0.083	0.435	26,633	0.187	0.444	-0.104***	-26.913
Accrual	25,222	-0.029	0.068	26,633	-0.028	0.063	-0.001***	-2.233
Ln(Analyst)	25,222	1.998	0.838	26,633	2.059	0.856	-0.061***	-8.199
Ln(Revision)	25,222	0.116	0.446	26,633	0.065	0.419	0.051***	13.403
Surprise Earnings	25,222	0.347	2.965	26,633	1.238	3.047	-0.891***	-33.745
Meet Expectation	25,222	0.638	0.480	26,633	0.784	0.411	-0.146***	-37.111
Negative Earnings	25,222	0.121	0.327	26,633	0.166	0.372	-0.045***	14.599
% Inst Own	25,222	0.711	0.276	26,633	0.728	0.271	-0.017***	-7.072

Table 3

Information Acquisition and Information in Earnings Calls

This table shows multiple regression results for the relationship between information acquisition via EDGAR and information in earnings calls. I use two different variables in measuring information in earnings calls: % QI which equals the percentage of numerical number in earnings calls. Net Tone is the percentage difference between positive words and negative words in earnings calls. For information acquisition, *IA[1,3]* which equals the natural log of total number of views for financial information in EDGAR in three days after the conference call. For columns (1) and (2), I only add firm and year fixed effect to determinate the base relationship between information acquisition activities and information insides earnings calls. I add control variables, which are described in Appendix II, in columns (3). I further use the interaction fixed effect between year and firm in column (4). Standard errors are clustered by firm and t-statistics are shown in parentheses. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1)	(2)	(3)	(4)
Dependent Variable	IA[1,3]	IA[1,3]	IA[1,3]	IA[1,3]
% QI	-0.031***		-0.024***	-0.051***
	(-3.97)		(-3.061)	(-4.322)
Net Tone		-0.090***	-0.073***	-0.064***
		(-10.615)	(-8.342)	(-5.108)
Afternoon			0.131***	0.087***
			(5.982)	(2.771)
Ln(Size)			0.199***	0.318***
			(11.294)	(6.676)
Book to Market			-0.043**	-0.176***
			(-2.307)	(-5.310)
Return on Asset			-0.515***	-0.474**
			(-3.344)	(-2.267)
Surprise Earnings			0.001	-0.000
			(0.901)	(-0.009)
Ln(Analyst)			0.039***	0.049*
			(2.870)	(1.848)
Ln(Revision)			0.029**	0.012
			(2.385)	(0.688)
Meet Expectation			-0.009	-0.004
			(-0.973)	(-0.318)
Negative Earnings			0.016	-0.006
			(0.994)	(-0.256)
Accrual			0.205***	0.415***
			(2.670)	(3.804)
Firm Risk			0.009	0.025
			(0.952)	(1.625)
% Inst Own			0.240***	0.281***
			(8.018)	(7.232)

Constant	1.957***	1.941***	0.512***	1.508***
	(27.97)	(28.321)	(3.747)	(4.212)
Year FE	YES	YES	YES	NO
Firm FE	YES	YES	YES	NO
Year FE*Firm FE	NO	NO	NO	YES
Observations	51,855	51,855	51,855	51,855
Adjusted R^2	0.635	0.636	0.641	0.667

Table 4

Instrument Method for Identification

This table reports my main 2SLS regression analysis based on instrumental variable method. The instrumental variable I choose is the weather condition on the earnings conference call date. Following previous literature, I use the cloud cover information as the proxy for weather condition. Panel A shows my first stage regression. Panel B reports the second stage regression for my information acquisition measurement. Standard errors are clustered by firm and t-statistics are shown in parentheses. Detailed definitions for each variable are provided in Appendix I. Significance level: *** p < 0:01, ** p < 0:05, * p < 0:1.

Panel A: First Stage

Dependent Variable	(1) % QI	(2) Net Tone
Daytime Cloud Cover	-0.006***	-0.008***
	(-4.808)	(-8.396)
Ln(Size)	0.134***	0.117***
	(7.165)	(9.493)
Book to Market	-0.120***	-0.167***
	(-5.884)	(-10.487)
Return on Asset	0.340**	0.727***
	(2.329)	(6.716)
Surprise Earnings	0.004***	0.015***
	(3.256)	(16.544)
Ln(Analyst)	-0.182***	-0.066***
	(-10.498)	(-5.678)
Ln(Revision)	-0.041***	-0.148***
	(-3.819)	(-17.077)
Meet Expectation	0.007	0.106***
	(0.985)	(17.018)
Negative Earnings	-0.023*	-0.041***
	(-1.654)	(-3.252)
Accrual	-0.178**	0.115**
	(-2.547)	(2.210)
Firm Risk	0.014*	0.167***
	(1.784)	(22.159)
% Inst Own	0.091***	0.042**
	(3.846)	(2.219)
Constant	1.952***	-0.027
	(14.459)	(-0.300)
Quarter FE	YES	YES
Firm FE	YES	YES

Observations	51,855	51,855
Adjusted R^2	0.571	0.501
1st Stage F-statistics	45.20	164.50
	(p<0.000)	(p<0.000)

Panel B: Second Stage Result for Indicator Variables

VARIABLES	(1) IA[1,3]	(2) IA[1,3]
Estimated %QI	-0.898***	-0.903***
	(-10.337)	(-8.538)
Estimated Net Tone	-0.719***	-1.030***
	(-5.048)	(-5.551)
Afternoon	0.131***	0.088***
	(5.977)	(2.792)
Ln(Size)	0.401***	0.506***
	(14.800)	(9.401)
Book to Market	-0.255***	-0.426***
	(-7.883)	(-8.466)
Return on Asset	0.287	0.554**
	(1.548)	(2.219)
Surprise Earnings	0.014***	0.018***
	(5.322)	(5.115)
Ln(Analyst)	-0.154***	-0.168***
	(-6.673)	(-4.713)
Ln(Revision)	-0.100***	-0.164***
	(-4.141)	(-5.046)
Meet Expectation	0.065***	0.104***
	(3.710)	(4.573)
Negative Earnings	-0.036**	-0.074***
	(-2.097)	(-3.008)
Accrual	-0.042	0.145
	(-0.491)	(1.200)
Firm Risk	0.132***	0.208***
	(5.190)	(6.033)
% Inst Own	0.306***	0.332***
	(10.040)	(8.457)
Constant	1.991***	3.369***
	(9.415)	(8.591)
Year FE	YES	NO
Firm FE	YES	NO
Year FE*Firm FE	NO	YES
Observations	51,855	51,855
Adjusted R^2	0.642	0.669

Table 5

Propensity Score Matching

This table reports my main regression analysis based on a sample in which earnings call with more quantitative or qualitative information is matched to calls with low quantitative or qualitative information. I use one-to-one match without replacement. I successfully find a match for 20,695 () firm-quarter observation in high quantitative (qualitative) information group which represents approximate 80% percent of my original firm-quarter observations in higher quantitative information group. Panel A shows my logit model to determine the score. Panel B lists my matched sample statistics. The regression results for the matched sample are shown in Panel C. Standard errors are clustered by firm and t-statistics are shown in parentheses. Detailed definitions for each variable are provided in Appendix I. Significance level: *** p < 0:01, ** p < 0:05, * p < 0:1.

Panel A: Prediction Model

	(1)	(1)
Dependent Variable	More Quantitative Info	More Qualitative Info
Afternoon	0.017**	0.008
	(2.249)	(0.394)
Ln(Size)	0.199***	0.042***
	(8.188)	(5.328)
Book to Market	0.881***	-0.297***
	(2.958)	(-11.747)
Return on Asset	0.013***	2.316***
	(3.505)	(7.525)
Surprise Earnings	-0.359***	0.044***
	(-22.285)	(11.716)
Ln(Analyst)	-0.357***	0.004
	(-15.344)	(0.238)
Ln(Revision)	0.006	-0.375***
	(0.249)	(-15.807)
Meet Expectation	-0.178***	0.448***
	(-5.564)	(17.917)
Negative Earnings	-0.611***	0.092***
	(-3.918)	(2.799)
Accrual	0.140***	-0.375**
	(5.965)	(-2.337)
Firm Risk	-0.026	0.461***
	(-0.667)	(18.743)
% Inst Own	0.203***	-0.007
	(9.812)	(-0.179)
Constant	-0.379**	-0.215
	(-2.540)	(-1.418)
Year FE	YES	YES

Industry FE	YES	YES
Observations	51,855	51,855
Pseudo R^2	0.0400	0.0720

Panel B: Summary Statistics for Matched Samples

Quantitative PSM	Treated	Control	t-statistics
Ln(Size)	7.488	7.494	-0.321
Book to Market	0.550	0.554	-0.923
Return on Asset	0.004	0.004	0.254
Afternoon	0.356	0.358	-0.425
Firm Risk	0.136	0.136	0.000
Accrual	-0.030	-0.030	0.000
Ln(Analyst)	2.042	2.039	0.366
Ln(Revision)	0.099	0.092	1.500
Surprise Earnings	0.815	0.808	0.234
Meet Expectation	0.714	0.715	-0.225
Negative Earnings	0.142	0.143	-0.291
% Inst Own	0.720	0.722	-0.744
N	20,695	20,695	
Qualitative PSM	**Treated**	**Control**	**t-statistics**
Ln(Size)	7.420	7.434	-0.741
Book to Market	0.546	0.540	1.424
Return on Asset	0.004	0.004	-0.086
Afternoon	0.352	0.356	-0.872
Firm Risk	0.125	0.127	-0.471
Accrual	-0.028	-0.028	0.323
Ln(Analyst)	2.003	2.015	-1.332
Ln(Revision)	0.080	0.083	-0.662
Surprise Earnings	0.746	0.757	-0.663
Meet Expectation	0.716	0.717	-0.264
Negative Earnings	0.145	0.146	-0.555
% Inst Own	0.721	0.723	-1.054
N	19,019	19,019	

Panel C: Regression Result for Balanced Sample

	(1)	(2)	(3)	(4)
	Quantitative PSM		Qualitative PSM	
VARIABLES	IA[1,3]	IA[1,3]	IA[1,3]	IA[1,3]
%QI	-0.024***	-0.051***	-0.021**	-0.050***
	(-2.835)	(-3.647)	(-2.354)	(-3.249)
Net Tone	-0.067***	-0.058***	-0.064***	-0.059***
	(-7.070)	(-3.883)	(-6.398)	(-3.495)
Afternoon	0.127***	0.113***	0.133***	0.078*
	(5.421)	(3.051)	(5.418)	(1.910)
Ln(Size)	0.191***	0.334***	0.198***	0.334***
	(10.201)	(5.678)	(10.211)	(5.393)
Book to Market	-0.034	-0.167***	-0.064***	-0.196***
	(-1.601)	(-4.048)	(-3.029)	(-4.060)
Return on Asset	-0.606***	-0.596**	-0.473***	-0.414
	(-3.504)	(-2.352)	(-2.592)	(-1.475)
Surprise Earnings	0.002	-0.001	0.003	-0.000
	(1.102)	(-0.420)	(1.581)	(-0.086)
Ln(Analyst)	0.041***	0.052	0.045***	0.027
	(2.669)	(1.587)	(2.937)	(0.806)
Ln(Revision)	0.030**	0.008	0.022	0.001
	(2.229)	(0.398)	(1.514)	(0.056)
Meet Expectation	-0.012	-0.005	-0.010	0.004
	(-1.097)	(-0.297)	(-0.876)	(0.273)
Negative Earnings	0.013	-0.011	0.011	0.008
	(0.759)	(-0.405)	(0.640)	(0.273)
Accrual	0.274***	0.484***	0.286***	0.496***
	(3.227)	(3.635)	(3.156)	(3.514)
Firm Risk	0.010	0.031	0.002	0.017
	(0.949)	(1.587)	(0.187)	(0.806)
% Inst Own	0.241***	0.236***	0.222***	0.279***
	(7.281)	(5.182)	(6.571)	(5.512)
Constant	0.539***	1.397***	0.480***	1.451***
	(3.661)	(3.177)	(3.162)	(3.156)
Year FE	YES	NO	YES	NO
Firm FE	YES	NO	YES	NO
Year FE*Firm FE	NO	YES	NO	YES
Observations	41,390	41,390	38,038	38,038
Adjusted R^2	0.638	0.664	0.631	0.660

Table 6

Channel Test

This table shows the estimated coefficients from a regression of information acquisition via EDGAR and information in earnings calls for small and large, low and high analyst following, and low and high readability index in earnings calls. Each quarter firms are sorted into two groups according to the quartile level of the variable. Group equals 1 if a firm belongs to bottom quartile for size and analyst following and top quartile for readability index. Detailed definitions for each variable are provided in Appendix II. Significance level: *** p < 0:01, ** p < 0:05, * p < 0:1.

	(1)	(2)	(3)	(4)	(5)	(6)
	High Fog Index		Small Firm		Less Analysts followed	
VARIABLES	IA[1,3]	IA[1,3]	IA[1,3]	IA[1,3]	IA[1,3]	IA[1,3]
% Numbers	-0.028***	-0.023***	-0.061***	-0.024***	-0.055***	-0.024***
	(-3.400)	(-2.947)	(-4.032)	(-3.077)	(-3.520)	(-3.070)
Net Tone	-0.073***	-0.097***	-0.073***	-0.096***	-0.073***	-0.098***
	(-8.314)	(-5.840)	(-8.339)	(-5.830)	(-8.339)	(-5.832)
% Numbers*Group	0.023*		0.033**		0.050***	
	(1.843)		(2.013)		(3.695)	
Net Tone*Group		0.031**		0.043**		0.026*
		(2.170)		(2.091)		(1.696)
Group	-0.046	-0.007	-0.162***	-0.064**	-0.088**	-0.023
	(-1.413)	(-0.539)	(-3.400)	(-2.210)	(-2.053)	(-1.007)
Controls	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Observations	51,855	51,855	51,855	51,855	51,855	51,855
Adjusted R^2	0.640	0.639	0.641	0.641	0.641	0.641

Table 7

Investor Reaction and Information Acquisition via EDGAR

This table shows multiple regression results for the relationship between information acquisition via EDGAR and cumulative abnormal return around each earnings conference call date. For column (1), I focus on the total information acquisition by all the investors. The result for institutional investors' information acquisition is presented in the second column. Standard errors are clustered by firm and t-statistics are shown in parentheses. Detailed definitions for each variable are provided in Appendix II. Significance level: *** p < 0:01, ** p < 0:05, * p < 0:1.

VARIABLES	(1) CARs(0,+3)	(2) Ln(Up Revision)	(3) Ln(Total Revision)
IA[1,3]	-0.199***	-0.019***	-0.018***
	(-3.466)	(-3.409)	(-5.083)
% Numbers	0.264***	0.070***	0.040***
	(3.133)	(9.027)	(7.594)
Net Tone	2.705***	0.094***	-0.019***
	(22.839)	(11.594)	(-3.310)
Controls	YES	YES	YES
Year FE	YES	YES	YES
Firm FE	YES	YES	YES
Observations	51,855	37,527	37,527
Adjusted R^2	0.105	0.347	0.651

Table 8

Number & Tone Management

This table reports my regression analysis based on Huang et al.(2014). Panel A reports the first stage regression by regressing the numerical information in earnings call on firm fundamentals. Panel B shows the result by using the residuals from panel A as the %QI in Table 3 to test whether investors' information acquisition behavior is affected by manager specific quantitative information usage. Standard errors are clustered by firm and t-statistics are shown in parentheses. Detailed definitions for each variable are provided in Appendix II. Significance level: *** p < 0:01, ** p < 0:05, * p < 0:1.

Panel A: First Stage

	(1)	(1)
Dependent Variable	% QI	Net Tone
Afternoon	0.062***	0.062***
	(3.045)	(3.045)
Ln(Size)	0.018	0.018
	(0.855)	(0.855)
Book to Market	-0.046**	-0.046**
	(-2.177)	(-2.177)
Return on Asset	0.621***	0.621***
	(4.445)	(4.445)
Surprise Earnings	0.004***	0.004***
	(3.168)	(3.168)
Ln(Analyst)	-0.177***	-0.177***
	(-10.492)	(-10.492)
Ln(Revision)	-0.008	-0.008
	(-0.796)	(-0.796)
Meet Expectation	0.010	0.010
	(1.357)	(1.357)
Negative Earnings	-0.025*	-0.025*
	(-1.791)	(-1.791)
Accrual	-0.505***	-0.505***
	(-7.694)	(-7.694)
Firm Risk	0.013	0.013
	(1.533)	(1.533)
% Inst Own	-0.103***	-0.103***
	(-3.673)	(-3.673)
Constant and FEs	YES	YES
Observations	51,855	51,855
Adjusted R^2	0.571	0.571

Panel B: Second Stage Result for Residual %QI & Net Tone

VARIABLES	(1) IA[1,3]	(2) IA[1,3]
Residual %QI	-0.026***	-0.055***
	(-3.300)	(-4.506)
Residual Net Tone	-0.075***	-0.064***
	(-8.339)	(-5.050)
Controls	YES	YES
Year FE	YES	NO
Firm FE	YES	NO
Year FE*Firm FE	NO	YES
Observations	51,855	51,855
Adjusted R^2	0.641	0.667

Table 9

Earnings Calls and Information Acquisition from Institutional Investor

This table shows multiple regression results for the relationship between information acquisition via EDGAR and information in earnings calls. I use two different variables in measuring information in earnings calls: % QI which equals the percentage of numerical number in earnings calls. Net Tone is the percentage difference between positive words and negative words in earnings calls. For information acquisition, IAInst[1,3] which equals the natural log of total number of views for financial information in EDGAR from institutional investors in three days after the conference call. For columns (1) and (2), I rerun the result in Table 3 by replacing IA[1,3] with IAInst[1,3]. Using the similar method as above, I replace the IA[1,3] with IAInst[1,3] in Table 3 and produce the last three columns. Standard errors are clustered by firm and t-statistics are shown in parentheses. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

VARIABLES	(1) IAInst[1,3]	(2) IAInst[1,3]	(3) CARs(0,+3)	(4) Ln(Up Revision)	(5) Ln(Total Revision)
IAInst[1,3]			-0.186***	-0.015**	-0.009**
			(-2.673)	(-2.422)	(-2.531)
%QI	-0.015***	-0.020**	0.266***	0.070***	0.040***
	(-2.694)	(-2.434)	(3.156)	(9.079)	(7.671)
Net Tone	-0.021***	-0.025**	2.716***	0.095***	-0.018***
	(-3.007)	(-2.504)	(22.903)	(11.753)	(-3.138)
Other Controls	YES	YES	YES	YES	YES
Year FE	YES	NO	YES	YES	YES
Firm FE	YES	NO	YES	YES	YES
Year FE*Firm FE	NO	YES	NO	NO	NO
Observations	51,855	51,855	51,855	51,855	51,855
Adjusted R^2	0.225	0.269	0.105	0.347	0.651

Table 10

Information Acquisition and Extreme Language in Earnings Calls

This table shows multiple regression results for the relationship between information acquisition via EDGAR and extreme language usage in earnings calls. I use two different variables in measuring information acquisition: IA[1,3] which equals the natural log of total number of views for financial information in EDGAR in three days after the conference call and IAInst[1,3] which is natural log of total number of views for financial information in EDGAR only for institutional investors in three days after the conference call. For the first two columns I use SignedExtreme and SignedModerate, which are the difference between positive extreme words (moderate words) and negative extreme words (moderate words). The last two columns I focus on the extremity measurement developed by Bochkay, Hales and Chava (2020). They define the positive (negative) extremity as the percentage of positive (negative) extreme words in total positive (negative) words. Standard errors are clustered by firm and t-statistics are shown in parentheses. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

VARIABLES	(1) IA[1,3]	(2) IAInst[1,3]	(3) IA[1,3]	(4) IAInst[1,3]
SignedExtreme	-0.094***	-0.045**		
	(-3.192)	(-1.999)		
SignedModerate	-0.015***	-0.010***		
	(-4.329)	(-3.700)		
ExtrWordsInPositive			-0.012***	-0.004
			(-2.690)	(-1.126)
ExtrWordsInNegative			0.004**	0.003**
			(2.081)	(2.100)
Other Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Observations	51,855	51,855	51,855	51,855
Adjusted R^2	0.648	0.226	0.647	0.225

Table 11

Robustness Check

This table reports my robustness check by adding two additional fixed effects to my original regression in Table 3. First two columns add additional days of week fixed effect to control for the fact that investors' preferences for leisure are stronger on Fridays, causing them to devote fewer resources to processing firms' disclosures. Last two columns introduce the call date fixed effect and focus on the effect that managers tend to report bad earnings news on busy days. Detailed definitions for each variable are provided in Appendix II. Significance level: *** p < 0:01, ** p < 0:05, * p < 0:1.

VARIABLES	(1) IA[1,3]	(2) IAInst[1,3]	(3) IA[1,3]	(4) IAInst[1,3]
% QI	-0.051***	-0.020**	-0.013**	-0.013**
	(-4.523)	(-2.473)	(-2.429)	(-2.569)
Net Tone	-0.060***	-0.023**	-0.054***	-0.013**
	(-5.079)	(-2.409)	(-8.384)	(-2.140)
Other Controls	YES	YES	YES	YES
Days of Week FE	YES	YES	NO	NO
Call Date FE	NO	NO	YES	YES
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Observations	51,855	51,855	51,459	51,459
Adjusted R^2	0.698	0.286	0.751	0.264

Appendix I

Procedures to Clean the EDGAR Log File

In this appendix, I will briefly introduce the EDGAR log file and express my procedures to obtain human views from raw data.

EDGAR Log Data

The raw EDGAR log files contain a record for each filling download request. The original data from SEC is in daily basis. Each daily data contains all the requests during that day and several important variables:

1) *ip*. Provided the first three octets of the IP address with the fourth octet obfuscated with a 3 character string.
2) *date*. The date for the log file.
3) *time.* The log file time in format (hh:mm:ss).
4) *code*. Status of the request.
5) *idx.* An indicator on whether the requester land the index page of a set of document.
6) *crawler*. And indicator variable on whether the user agent self-identifies as an robot.
7) *cik.* The SEC central index key associated with the document requested.

The Procedure to Clean the EDGAR data

I follow the procedures introduced by Ryans (2017) to filter all the robot views since they are irrelevant to my study. The detail steps are listed below:

1) Keep only with *code* = 200 which stands for successful delivery of requested document.
2) Keep records with *idx* = 0 which will remove all the views in the index pages.
3) Keep records with *crawler* = 0 which will remove all the views from identified web crawlers by SEC.
4) Keep only IPs with any downloads per minutes smaller than 25.
5) Keep only IPs with number of CIK's downloaded per minute smaller than 3.
6) Keep only IPs with number of downloads smaller than 500 during a day.

Appendix II

Variable Definitions

Variable	Definition
Ln(Size)	Natural log of the firm's total assets
Book to Market	Book equity over market equity
Return on Asset	Net income over assets
Net Tone	The difference between the number of positive words and negative words in earnings call transcripts, scaled by the total number of words
% QI	Total number of numeric phrases in earnings call transcripts, over the sum of the count of words and numbers
Afternoon	An indicator variable to distinguish between a morning earnings conference call and an afternoon earnings conference call
Firm Risk	Natural log of the standard deviation of ROA over the past ten years
Accrual	Quarterly accruals over total assets. Accruals are defined as IBCY-OANCFY using quarterly Compustat data
Ln(Analyst)	Natural log of the number of analysts following the firm during the quarter of the company’s earning
Ln(Revision)	Natural log of the mean number of earnings estimate revisions by each analyst during the quarter for the company
SignedExtreme	Difference between extreme positive words and extreme negative words in terms of total words in earnings conference calls
SignedModerate	Difference between moderate positive words and moderate negative words in terms of total words in earnings conference calls
Surprise Earnings	The difference between actual earnings and consensus analysts’ forecast divided by the standard deviation of analysts’ forecasts
Meet Expectation	A dummy variable equal to one if the firm meets analyst earnings expectation in that quarter
Negative Earnings	An indicator variable equal to one if the firm has negative earnings in that quarter
Total Views	Total Downloads for financial filings from SEC’s website
Total Inst Views	Total Institutional Downloads for financial filings from SEC’s website
Total Revision	Total numbers of revision made by analysts within 10 days after earnings conference calls
Up Revision	Total numbers of up revision made by analysts within 10days after earnings conference calls
IA[1,3]	Ln(Total Downloads)
IAInst[1,3]	Ln(Total Inst Downloads)
Ln(Up Revision)	Ln(Up Revision)
Ln(Total Revision)	Ln(Total Revision)
% Inst Own	The percentage of institutional holdings based on the most recent 13-F institutional ownership report issued

ExtrWordsInPositive	Proportion of extreme positive words to total positive words in the earnings conference call
ExtrWordsInNegative	Proportion of extreme negative words to total negative words in the earnings conference call
CARs(0,+3)	Cumulative Abnormal Return from 0 days to +3 days around the earnings conference call date