# Temporal Focus in Earnings Conference Calls*

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VERY PRELIMINARY – COMMENTS WELCOME

**Abstract**

This paper examines the role of temporal focus (future vs. past orientation) in managerial communication on earnings conference calls. Employing a carefully validated machine learning approach, we construct a proxy of "Future minus Past ($FMP$)" talk at the sentence level. Presentations on average are more focused on the past and answers to analyst questions are more focused on the future. This appears to constitute a communication norm, deviations from which are penalized. Stock prices respond negatively to $FMP$ in presentations, even though future talk is generally more upbeat. By contrast, the market responds positively to $FMP$ in answers to analyst questions. The stock-price reactions match with analyst responses and changes in uncertainty, and they are not explained by the tone of the future- and past-oriented information. We find that managers tend to deviate from "normal" temporal focus after poor earnings and bad returns. Such deviations also predict poor future earnings. Thus, deviating from "normal" temporal focus appears to be a managerial tactic to avoid uncomfortable discussions. In support of this view, high $FMP$ in presentations (answers) engenders more negative (less positive) responses when employed in firms with poor governance. Overall, the temporal focus of managers emerges as an important and revealing feature of managerial communication.

**Keywords:** Corporate communication, Earnings conference calls, Machine learning, Manager style, Temporal focus, Textual analysis

**JEL Codes:** G14, G30

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## 1 Introduction

Time plays a critical role in finance. Receiving more future-oriented information should be of interest to investors: First, only expected future cash flows should matter for the valuation of an asset. Second, future outcomes are uncertain, so knowing more about them may reduce the discount rate. However, deeper insights about past quarters may also be of value, particularly when performance was unusual, given that the future is not independent of the past. This paper examines the determinants and consequences of *temporal focus* of managers, that is, how much they focus on the future vs the past in their communication. It emphasizes the idea that the expectations of investors of when managers should talk about the past, and when about the future, play a major role.

Earnings conference calls provide an ideal setting for analyzing temporal focus. Naturally, because they happen in the context of the announcement of the elapsed quarter's earnings, managers will surely to some extent refer to the past, at least in the scripted presentation at the beginning of the call. However, managers have a choice regarding the extent to which they do this. Moreover, especially in the relatively more improvised questions and answers (Q&A) part, managers may choose to answer analyst questions by referring to either the past or the future. The literature has provided comprehensive evidence of the overall informativeness of conference calls (Bowen et al. (2002), Brown et al. (2004), Kimbrough (2005), Matsumoto et al. (2011)).[1] Different linguistic features of conference calls affect analyst responses (e.g., stock recommendation revisions, earnings forecasts) and market reactions (e.g., abnormal returns, bid-ask spreads, trading volume).[2]

[1]In October 2000, a new regulation from the Securities and Exchange Commission (SEC) took effect to prohibit the disclosure of non-public information to a selective group (Regulation FD). Conference calls which used to be mainly accessible only to institutional investors and financial analysts have since then reached a much broader audience.

[2]For example, linguistic features such as managerial tone (Price et al. (2012), Huang et al. (2014), Davis et al. (2015), Brockman et al. (2015), Druz et al. (2020)), managerial vocal cues (Mayew & Venkatachalam (2012)), interaction between managers and analysts (Hollander et al. (2010), Chen et al. (2016)), short-termism (Brochet et al. (2015)), managers' lack of spontaneity (Lee (2016)), contrastive words (Palmon et al. (2016)), clarity (Dzieliński et al. (2017)), humor (Call et al. (2019)), headline salience (Huang et al. (2018)), extreme words (Bochkay et al. (2020)), and euphemism(Suslava (2021)) have been analysed.

In this paper, we analyze the temporal focus of the managerial communication on earnings conference calls. Temporal focus is an important concept in the psychological literature (see, e.g., Shipp et al. (2009), Shipp & Cole (2015), Shipp & Aeon (2019)). The temporal focus of individuals impacts how they attend to information, and it could conversely influence investors' interpretation of the information. This motivates us to study the supply of information with different temporal foci as well as its implication for investors and analysts in the corporate communication setting.

We begin by developing a novel measure of temporal focus. Previous literature applies a dictionary-based approach to extract forward-looking statements in financial disclosures (Li (2010), Matsumoto et al. (2011), Muslu et al. (2015), Bozanic et al. (2018)). We go beyond these important works in two important dimensions. First, we also consider information concerning the past and thus calibrate future orientation with the extent to which a company communicates about the past. Second, contrary to a simple keyword search, we introduce part-of-speech (POS) tagging[3] to expand the rule set of identifying the time-reference of each sentence.

The first step in developing the measure is to classify each sentence into one of five temporal groups: past, present, future, "modal verb", and "no verb" ("modal verb" and "no verb" are further grouped as undefined). Drawing on prior literature, we develop a set of classification rules described in detail in Section 4. We evaluate the performance of our rule-based algorithm on a manually labeled test set of 1,200 sentences randomly drawn from our sample of earnings calls. The rule-based algorithm achieves an overall accuracy score of 0.88, meaning that 88% of the its predictions regarding temporal focus are correct. Using this result as a benchmark, we train several machine learning algorithms to identify the time-reference of the sentences. The XGBoost model provides us with the best out-of-sample results with an accuracy score of 0.90, slightly beating the rule-based benchmark.

Based on the results from the best-performing machine learning algorithm, we then define Future minus Past ($FMP$) as the difference between the fraction of future-oriented

[3] A part of speech (POS) is a category of words which share similar grammatically properties. Common POS tags include verb, noun, adjective, adverb, pronoun, preposition, conjunction, etc.

sentences and past-oriented sentences. The measure ranges between -1 and 1, and a positive value indicates that managers focus more on the future compared to the past. $FMP^P$ and $FMP^A$ denote the values in presentations and answers, respectively. Importantly, on average managers focus more on the past during the presentation, but more on the future during the Q&A section. Specifically, $FMP^P$ ($FMP^A$) has a mean of minus 15.7% (plus 4%), meaning that among the total number of sentences that managers use during the presentations (answers), the fraction of future-oriented sentences is 15 (4) percentage points lower (higher) than the fraction of past-oriented sentences.

How do investors react to $FMP$? The answer is not obvious, since $FMP$ does not have a clear directional economic meaning (contrary to, say, linguistic tone). The differences in average $FMP$ between the presentation and the Q&A motivates us to form a hypothesis from a psychological perspective. In the typical conference call, the discussion of the past (the main temporal focus in the presentation) precedes the discussion of the future (the main focus in the answers). Previous literature shows that such a sequence also exists in other corporate disclosure settings such as earnings press releases and shareholder letters (Emett (2019)).

Such a pervasive structure of temporal focus in corporate communication suggests the existence of a social norm, a concept of the psychological literature, where the idea is widely adopted to explain individual or collective human behavior (Sherif (1936), and Cialdini & Trost (1998)). Norms form in an evolutionary manner in the sense that efficient, relevant, and informative behavior or beliefs are performed and rewarded repeatedly through reinforcement learning or a feedback system (Berger (1967), Opp (1982), Schaller & Latané (1996), and Thibaut & Kelley (2017)). A direct consequence is that following the norm will be considered desirable and rewarded while deviating from the norm will be regulated and punished. Such feedback materializes either indirectly through social pressure or directly through the legal system when the norm becomes a law.

In the setting of corporate communication, past information (realized and factual) is crucial to provide the context for the future (hypothetical or conjectural) discussions. The future talk will be difficult to interpret without context from past-relevant information, leading to inefficient communication and possible misinterpretation. In addition, a mismatch between managers' information supply with one temporal focus and investors' information demand for another indicates an information asymmetry problem. In such a situation, investors will find it more risky to forecast future cash-flows and will demand higher expected returns as compensation (Barry & Brown (1986), Merton (1987), Botosan (1997), Healy & Palepu (2001), and Fang & Peress (2009)).

Therefore, we hypothesize that investors react negatively towards managers' deviation from expected past focus in the presentation, and positively towards managers' complying with expected future focus during the Q&A session. We find strong evidence for this prediction. Moreover, the market reaction towards $FMP$ is less negative (more positive) for growth firms than value firms. This provides additional evidence that the market responds positively when the temporal focus of information supply matches the investors' expectations.

Consistently, we also find that $FMP^P$ increases the return volatility, the bid-ask spread, and analysts' forecast error, suggesting that focusing more on the future in the presentation increases uncertainty and information asymmetry. By contrast, $FMP^A$ converges analysts' opinions and reduces forecast error.

What information does $FMP$ contain? And under which circumstances do managers choose to deviate from the norm despite the negative market feedback?

To answer, we first investigate the relation between $FMP$ and firms' future expected and realized operating performance. Analysts adjust their earnings forecast downwards if the managers put more relative focus on the future during the presentation. Consistently, $FMP^P$ is negatively correlated with the actual earnings change in the coming quarters, meaning that the more managers focus on the future compared to the past in the conference call presentation, the worse the firm's future performance will be. (We do not claim causality of this relation.)

Do managers directly communicate negative information through their future focus? The evidence from the determinants of managers' choice of temporal focus points to a negative answer. First, managers talk less about the future when they speak with a negative tone, suggesting that managers may try to disconnect negative sentiment from future-oriented information. Second, managers increase their future focus in the presentation section of earnings conference calls when the firm experienced poor earnings and bad returns in the recent quarter. Combined, these results suggest that the negative association between $FMP^P$ and future earnings is not primarily due to managers revealing negative information directly. Rather, firms whose managers avoid discussing negative past performance by focusing on the more optimistic future appear to suffer from an agency problem that manifests itself in worse future operating outcomes.

Consistent with this interpretatoin, the market reaction towards $FMP$ is less negative (more positive) for firms with higher institutional ownership, more capable managers, or when managers' interests are more aligned with those of the shareholders. These results suggest that investors consider managers' deviation from the communication norm a managerial tactic, but punish it less when they think the managers are more credible.

Overall, the study reveals that relative temporal focus ($FMP$) is an important feature of managerial communication and provides incremental information for analysts and investors.

This paper contributes to the literature in four ways. First, we expand the literature by analyzing the information content of temporal focus. Previous research has focused on forward-looking statements (Li (2010), Matsumoto et al. (2011), Muslu et al. (2015), Bozanic et al. (2018)). Our paper takes both future and past orientation into consideration. This is a potentially important innovation because a given amount of future-oriented statements is likely to contain different information whether it goes hand in hand with a large or a small number of past-oriented statements.[4] Moreover, we provide evidence that the temporal focus explains not only the absolute, unsigned strength of market reactions, but also the *direction*.

Second, we contribute to the literature on corporate disclosure by providing empirical evidence regarding the different functionality of presentations and answers in earnings

[4]As an analogy, when considering managerial sentiment, using the fraction of negative words in total words ignores the fact that a manager may simply use more negative *and* positive words. See Price et al. (2012) and Druz et al. (2020).

conference calls. While prior studies have sometimes distinguished between presentations and answers (e.g., Brockman et al. (2015), Druz et al. (2020)), they tend to find the same directional effects. We show that the information with the same linguistic feature provided by the presentation and the Q&A section can generate opposite effects on the stock price. These different reactions are not only in line with the theoretical prediction regarding the prevailing norms in the two parts of the conference call, but they also line up with changes in expected future cash flows and uncertainty. Thus, they seem to pick up differences in fundamental implications of temporal focus and expectations of market participants regarding temporal focus in different parts of the conference calls.

Third, we add to the financial textual analysis literature by applying machine learning methods with more advanced linguistic features such as part-of-speech tagging, word embedding, and n-grams. Prior research uses a key-word searching approach and heavily depends on a specific list of key-words.[5] Using machine learning methods helps to learn more general rules and reduces error when such lists are difficult to prove to be exhaustive. We also show that the machine learning approach only slightly beats the rule-based one, implying the traditional rule-based method is a good benchmark approach itself in this application.

Fourth, we add to the management literature regarding the temporal focus of the managers. Prior literature mainly discusses how the temporal focus of executives has consequential effects on managerial behavior and firm operations (Nadkarni & Chen (2014), Gamache & McNamara (2019), and DesJardine & Shi (2021)). Our focus instead is on investor and analyst reactions.

The remainder of this paper proceeds as follows. Section 3 describes the sample and basic summary statistics. Section 4 develops our measure of temporal focus and compares it with measures of forward-looking statements in the literature. Section 5 presents the main empirical results. Section 6 concludes.

[5] Li (2010), Matsumoto et al. (2011), and Bozanic et al. (2018) use a pure dictionary-based approach. Muslu et al. (2015) relies on additional rules based on the year referred to in the statements and the exact year of the corporate filing.

## 2 Literature and Hypotheses Development

Previous literature on corporate disclosure has touched upon the notion of temporal focus primarily in the context of forward-looking statements (FLS). The findings generally confirm that FLS contains useful information and companies with more FLS in their disclosure also have more informative prices.[6] Besides studying FLS in general, studies such as Brochet et al. (2015) also make a more granular distinction between short-term and long-term FLS. Using a textual measure of disclosure time horizon in earnings conference calls, Brochet et al. (2015) show that it is related to myopic managerial behavior.

In parallel to the finance and accounting literature, the management literature considers temporal features in corporate disclosures from a different perspective. Psychological research argues that attention to the past, present, and future is a distinct personality trait (Bluedorn (2002), Shipp et al. (2009), Shipp & Aeon (2019)). Therefore, this strand of research considers temporal focus as a characteristic of the managers rather than the company's information environment. In this case, in addition to the future, the past and the present are also analyzed as separate dimensions, in order to understand the managerial decisions of the executives. The temporal focus of managers influences their decision-making by impacting the information field of managers and what they focus on.[7]

Despite the growing number of studies of temporal features in the corporate setting, one economically important question, the directional market reaction to such feature, has not been analyzed. The literature has studied the relation between the temporal feature

[6] For the analysis of the content of FLS, Li (2010) finds that the positive tone in forward-looking statements (FLS) in the Management Discussion and Analysis (MD&A) section of 10-K and 10-Q filings predicts better earnings in the coming quarters. For the impact of the quantity of FLS, Muslu et al. (2015) show that FLS in MD&A of 10-K filings improves the informational efficiency of stock prices, meaning making the stock price better reflect the future earnings information. Bozanic et al. (2018) find that more non-forecast-like forward-looking statements in earnings announcements are related to improvements in the accuracy of analyst earnings estimates and the level of stock price reaction.

[7] Nadkarni & Chen (2014) find that CEOs' temporal focus impact the rate of new product introduction conditional on the environment dynamism. For example, they show that products are introduced faster by firms headed by CEOs with low past focus and high future/present focus in a dynamic environment. Gamache & McNamara (2019) analyze the impact of CEOs' temporal focus on how firms react to negative media coverage of acquisitions. They find that the negative relationship between negative media reaction and subsequent acquisition spending is stronger (weaker) for CEOs with a high past (future) focus. DesJardine & Shi (2021) provide evidence that CEOs' temporal focus also impacts the effect of executive compensation on their risk-taking.

and the information environment, the absolute magnitude of market activity, managerial behavior, and firm operations. One possible reason, as pointed out in Bozanic et al. (2018) is that *"...the amount of forward-looking disclosure is not an unambiguously positive or negative signal (unlike, for example, disclosure tone or signed earnings surprise)..."* Thus, the ambiguous nature of temporal feature of information itself makes its impact on the stock price not immediately clear.

Indeed, one could argue that $FMP$ as well as $FMP^P$ and $FMP^A$ are unrelated to market reactions conditional on the content of the earnings information (both quantitatively, in terms of the earnings surprise, and qualitatively, in terms of the linguistic tone of the call). Thus, under this baseline hypothesis what matters is the content of the news (good vs. bad) not the time orientation per se.

***H0 (Null Hypothesis):*** Both $FMP^P$ and $FMP^A$ are unrelated to stock price reactions and analyst reactions.

However, the psychology literature suggests there could well exist an expectation, a communication norm, among recipients of different types of corporate disclosure as to what their temporal focus should be. Deviations from this norm could then elicit negative market responses to temporal focus as such.[8]

This motivates us to first hypothesize what the communication norm regarding temporal focus could be and to investigate directional market responses. Secondly, if directional market responses indeed point to the existence of a communication norm, what could be the economic mechanisms motivating managers to adhere or deviate from it?

### 2.1 The Communication Norm of Temporal Focus in Earnings Conference Calls

The structure of earnings conference calls – a prepared presentation followed by a more improvised Q&A session where analysts can bring up questions – raises the natural question of whether there are systematic differences of temporal focus in the two sections.

[8] A hint that this might indeed be going on is found in Muslu et al. (2015) Table 3, Panel B, which shows that the abnormal forward-looking intensity is negatively associated with the 10-K filing returns and implies a directional relation between a temporal focus of information and stock price. However, this is not the primary focus of their analysis and is not directly interpreted in the paper.

Anecdotal evidence seems to show specific patterns of the distribution of temporal focus along with the development of communication. For example, Emett (2019) provides evidence in a corporate setting by implementing a qualitative analysis of earnings press releases and shareholder letters from 25 large companies. He finds that discussions of current performance typically precede discussions of the firm's strategy and plans for the future within firm disclosure.

The same appears to be true for earnings conference calls. The following opening passage from Burlington Coat Factory Q1 2014 Earnings Conference Call exemplifies the typical structure:

*"Tom [Kingsbury, Chairman&CEO] will begin with a brief overview of the quarter's financial results and discuss some recent developments while providing a discussion of our ongoing transformation. Todd [Weyhrich, CFO] will then review our financial results and future outlook in more detail before we open the call for questions."*

Indeed, the temporal focus is initially on the past. It shifts to the future as the call progresses. The pervasiveness of such structure leads us to hypothesize that there exists a communication norm regarding the distribution of temporal focus. The idea of "*norm*" is widely applied in the psychology research to help describe and explain human behavior (Cialdini & Trost (1998)). Sherif (1936) characterizes the concept as "*customs, traditions, standards, rules, values, fashions, and all other criteria of conduct which are standardized as a consequence of the contact of individuals.*" Therefore, a norm is intrinsically related to expectations regarding how things should be from a social perspective. The formation of norms can be explained from an evolutionary viewpoint as a result of "trial and error" and reinforcement learning (Thibaut & Kelley (2017)), where certain behaviour or belief becomes a norm when they are performed and rewarded repeatedly (Opp (1982), Berger (1967)), and perceived as effective, relevant and informative (Schaller & Latané (1996)). In addition, Opp (1982) and Cialdini & Trost (1998) point out that members of the social network will regulate deviations from the norm by telling the deviants what they should do. An ultimate form of a norm may be established by the enactment of a new law. In many cases, the norms may not be explicitly stated and sanctions of deviations are not enforced by the legal system.

Financial markets provide direct feedback towards the communicative behavior of managers. We expect certain types of temporal focus to be likely to be rewarded more given the nature of information transmission. Past information (realized and factual) helps to provide the context of the company on which statements of the future (hypothetical or conjectural) could be built upon. Without necessary context, the information transmitted from management to the audience of analysts and investors could be inefficient and prone to misinterpretation. Therefore, we expect the basic communication norm to be a low future minus past average in presentations (which come first), and a higher future minus past average in answers. To the extent that the deviation from the communication norm in a given part leaves the information demand of investors and analysts unsatisfied, this leads to increased uncertainty. The relation between information disclosure and cost of capital has been widely researched in the literature (Botosan (1997)). The argument is that when information is not complete, forecasting future cash flows is more risky and investors will demand a premium for bearing such information risk (Barry & Brown (1986) and Healy & Palepu (2001)), in line with Merton (1987).

Summarizing, we posit the following hypothesis:

***H1 (Communication Norm Hypothesis):*** Investors and analysts expect managers to focus more on the past in the presentation, and more on the future in the Q&A during earnings conference calls. Deviating from this norm will trigger negative responses.

- *H1.A (Investors' Reaction):* Stock prices respond negatively towards $FMP^P$, but positively to $FMP^A$.
- *H1.B (Analysts' Reaction):* Analysts' earnings forecasts respond negatively towards $FMP^P$, but positively to $FMP^A$.
- *H1.C (Market Uncertainty and Information Asymmetry):* $FMP^P$ increases a firm's stock volatility, bid-ask spread, analyst forecast dispersion, and analyst forecast error. $FMP^A$ has the opposite effect.

## 2.2 Information Content of Temporal Focus in Earnings Conference Calls

The existence of a communication norm with respect to temporal focus on earnings calls raises the question of why might managers deviate from it. If managers are rational about the fact that deviating from the audiences' expectation incurs a negative market reaction (assuming Hypothesis 1 holds), but they still do it anyway, this indicates that they are revealing information through it, or that this behavior may come as a result of managers' attempt to avoid something even more unpleasant.

As for the first possibility, $FMP$ in presentations may directly suggest lower future operating performance of the company. If that is so, we would expect $FMP^P$ to also be associated with higher linguistic negativity, which prior literature has identified as an important marker of deteriorating future performance Druz et al. (2020). The opposite relation would hold for $FMP^A$, that is, it should predict higher future performance, and it should go along with more positive statements. Summarizing:

***H2 (Managerial Information Hypothesis):*** A deviation from the communication norm indicates information about future performance.

- *H2.A (Operating Performance):* Higher $FMP^P$ ($FMP^A$) is associated with lower (higher) future cash-flows.
- *H2.B (Managers' Choice of $FMP$):* Managers are more likely to choose higher $FMP^P$ ($FMP^A$) when they speak more negatively (positively).

More broadly, $FMP$ may also be a proxy for other processes going on at the firm. For example, managers may shift focus to the future when they want to avoid discussing current problems. This could signal that they do not fully understand the reasons for the disappointing performance and therefore avoid discussing it. At the same time, this would make potential remedies, which the managers may bring up in their more extensive future-oriented talk, less likely to succeed, thus contributing to repeated disappointments in subsequent quarters. Thus, $FMP$ does not have a direct causal effect on performance, but is simply a correlate.

The second possibility is that managers deviate from the communication norm to avoid discussing unfavorable information. Thus, they employ $FMP$ as a managerial tactic. Prior literature indeed emphasizes that corporate disclosure is ripe with agency issues (Graham et al. (2005)). For example, firms tend to withhold bad news, for example, to protect their compensation (Kothari et al. (2009)) or due to career concerns (Nagar (1999), Nagar et al. (2003)).

Existing research highlights a number of tactics and linguistic patterns managers apply.[9] In particular, Matsumoto et al. (2011) find that managers use more forward-looking statements when firm performance is poor. This can be seen as managers may find it uncomfortable to discuss the past bad performance.

Thus, under the managerial tactics hypothesis, higher $FMP$ in presentations would again portend worse performance because an agency problem is likely to lead to worse operating performance for the firm, like under the managerial information hypothesis. However, if agency is the driving factor, we would expect managers to speak more *positively* when they employ more $FMP^P$, contrary to the managerial information hypothesis. Thus, the relation between linguistic tone and $FMP$ helps distinguish between the two hypotheses.

Finally, investor responses can also shed some light on this hypothesis. Specifically, we expect investors to respond most negatively to deviations from the communication norm when corporate governance is poor.[10]

Overall, as an alternative to H2, we expect the following:

[9]Such tactics include complicating corporate disclosure (Li (2008)), not answering questions from the analysts (Hollander et al. (2010)), tone management (Huang et al. (2014)), sticking to the scripts (Lee (2016)), headline salience manipulation (Huang et al. (2018)), and use of euphemism (Suslava (2021)).

[10]The existing evidence on whether investors see through managerial tactics is mixed. Some studies find that investors may not be fully aware of managers' opportunistic incentives and only adjust their behavior in the long run. For example, Suslava (2021) find that investors under-estimate the extent of negative information in managers' use of euphemism. Huang et al. (2014), and Huang et al. (2018) find that investors over-react to earnings information when managers use abnormal positive tone or strategically make good earnings news more salient in the headlines. For some other managerial tactics, the investors may be able to tell the negative implications and react immediately. For example, Lee (2016) find that investors recognize managers' adherence to predetermined scripts and lack of spontaneity as a way to hide private negative information, and an immediate negative market response follows such a tactic.

***H3 (Managerial Tactics Hypothesis):*** Managers deviate from the communication norm to avoid revealing unfavorable information or to distract from it.

- *H3.A (Operating Performance):* Higher Higher $FMP^P$ ($FMP^A$) is associated with lower (higher) future cash-flows.
- *H3.B (Managers' Choice of $FMP$):* Managers are more likely to choose higher $FMP$ when they speak more positively.
- *H3.C (Stock Price Reactions):* Investors react less favorably to $FMP$ in poorly governed companies.

## 3 Sample and Basic Summary Statistics

Earnings conference call transcripts are obtained from Refinitiv Company Events Coverage (previously known as Thomson Reuters Street Events). Each transcript has a unique event id and comes in XML format. We use Python to process the transcripts. Firstly the meta-data of the transcript is extracted, which includes the identifiers of the company (CUSIP, company name, and exchange ticker) and the exact time when the call is held. We use all available transcripts, obtaining a sample period from 2002 to 2020.

We next retrieve financial data from WRDS. Stock price information is obtained from CRSP, fundamentals are retrieved from COMPUSTAT, and the earnings and analyst forecasts come from IBES. The CRSP data is firstly merged with COMPUSTAT data through the CCM linking table provided by WRDS. Then IBES data is merged to CRSP data by constructing a similarly linking table based on the secondary identifiers of the two datasets.[11] Finally, through the identifiers provided by the earnings conference calls (CUSIP, company name, and exchange ticker), we merge the financial data to the earnings conference calls transcripts data. Overall, we have 157'360 firm-quarter observations for 4'964 unique firms in the sample.

[11] We adapt the Python code provided by WRDS to construct the linking table between CRSP and IBES. `https://wrds-www.wharton.upenn.edu/pages/support/applications/python-replications/linking-ibes-and-crsp-data-python/`

Variable definitions are presented in Appendix A1. Panel A of Table 1 reports the summary statistics for firm characteristics. Comparing the median $SIZE$ and $BTM$ of the sample with the numbers obtained from the COMPUSTAT universe during the same periods (not tabulated) suggests that our sample is somewhat tilted towards large-cap and growth firms. This could be because large and growth firms are more likely to hold earnings conference calls than small and value firms. Panel B shows the linguistic characteristics captured from conferences calls. (The construction of the key variable $FMP$ is discussed in Section 4.)

- Table 1 -

Panel C compares the sector composition of our sample and the COMPUSTAT universe. We observe that overall the distribution of firms from different sectors of our sample is not too different from the counterpart of COMPUSTAT. Our sample has relatively more firms from the health care and information technology sector and fewer from the energy and financial sectors. Panel D reports the number of firms and earnings conference calls each year. Except for the year 2002 which has relatively less earnings conference calls in the database, the observations are evenly distributed across the years.

## 4 Measuring Temporal Focus

To measure temporal focus, we proceed in two steps. As a starting point, our rule-based algorithm, described in Section 4.1, classifies each sentence into temporal groups such as past, present, and future. We then take this classification as an input into a machine learning approach, described in Section 4.2. Section 4.3 provides basic descriptives of the key measure we define. Section 4.4 highlights how managerial temporal focus typically differs between the presentation and Q&A part of conference calls.

We parse earnings conference call transcripts in several stages depicted in Figure A1. A typical earnings conference call transcript contains a header with meta-information such as company identifier and the time of the call, which we use to merge with firm-level financial variables. The textual content of the call is usually divided into presentation and Q&A section. Crucially, each passage is attributed to a particular speaker, which allows us to identify whether it comes from a manager or from an analyst. We use this information to construct linguistic features separately for the following parts of the call: presentation (given by managers), analysts' questions and managers' answers.

## 4.1 Rule-based Approach

### 4.1.1 Identifying time-reference with part-of-speech tags

Existing financial and accounting literature has mainly focused on detecting future-oriented information. Specifically, A set of rules such as searching for future related words are applied to identify forward-looking statements in various types of corporate disclosure (Li (2010), Matsumoto et al. (2011), Muslu et al. (2015), Bozanic et al. (2018)). Building on previous literature, we want to have a more comprehensive understanding of the different time dimensions of information, and this motivates us to use more generic linguistic features to extract such information. Specifically, we separate every sentence into tokens and extract the part-of-speech tags of each token with Python's NLP library Spacy.[12] Parts of speech (POS), also known as word classes or lexical categories, are defined groups of words that have similar grammatical properties. The most common POS groups include verbs, noun and adjectives.

Panel A of Table A2 presents an example of the POS tagging[13] output for the sentence: *"We achieved $1.21 billion in Digital Media revenue in Q2, a 29% increase year-over-year."*, which is a frequently used type sentence of in earnings conference calls. The POS tag VBD for the verb *"achieved"* indicates that the grammatical tense of the sentence is past simple.

- Table A2 -

[12]Spacy is a leading natural language processing library in python and is widely used in both academia and industry. It has integrated a powerful and robust POS tagging functionality within its NLP pipeline. Compared to other more traditional NLP libraries such as NLTK, it better supports machine learning tasks and provides useful features such as word vectors. To address the concern of library-specific effect, we also compare Spacy and NLTK and find that the rule-based measure generated from both libraries are very similar.

[13]The complete list of descriptions of POS tags can be found at `https://www.ling.upenn.edu/courses/Fall_2003/ling001/penn_treebank_pos.html`

In this paper, we categorize the time reference of sentences into five groups, i.e. past, present, future, and undefined (MD or NAN)[14]. Panel B of Table A2 presents a few examples of each category. We improve the existing methods by using additional information from the POS tag of the verbs. We determine the temporal focus of a sentence in 4 steps.

1. Determine whether the sentence is of future temporal focus:
   - The sentence includes modal verb (MD) "*will*".
   - The sentence includes phrases "*am/is/are* + present participle (VBG)".
   - The sentence includes verb form (VBZ, VBP, VBN, VB) of keywords "*aim*", "*anticipate*","*assume*","*commit*","*estimate*","*expect*","*forecast*","*foresee*", "*hope*", "*intend*", "*plan*", "*project*", "*seek*", and "*target*".
2. If not, determine whether the sentence is of past temporal focus:
   - The sentence includes past tense for verb (VBD).
   - The sentence includes phrases "*have/has* + past participle (VBN)".
3. If not, determine whether the sentence is of present temporal focus:
   - The sentence includes present tense for verb (VBZ or VBP).
4. Finally, we put the remaining sentences into the undefined category:
   - MD subcategory: The sentence includes modal verbs (MD) other than "*will*".
   - NAN subcategory: The sentence doesn't have any verbs.

A complication arises when there are multiple verbs in the same sentence. For example, in the sentence "*And we* ***expected*** *over time on average, it* ***will*** *be relatively in line with net income.*", both modal verb (MD) "will" and past simplw (VBD) "expected" will be detected by the algorithm. When multiple verb tenses are detected in the same

[14]For the undefined label, we distinguish between two cases: sentence only with modal verbs (MD) or sentence with no verbs (NAN)

sentence, our algorithm prioritizes future tense in determining the temporal focus of the sentence, followed by past tense, and finally present tense.

The key differences of our rule-based approaches with respect to prior studies are:

1. we consider present continuous (e.g. "*We**'re working** on that now as part of our business plan.*") as part of future focus

2. we use POS tagging to make sure we only capture verb forms of the keywords listed above as part of future focus

### 4.1.2 Validation with manually labeled sample

One of the traditional challenges of analyzing the economic implication of linguistic features is to disentangle the validity test of the measure itself as a good proxy for the latent variable of interest, and the test of economic hypothesis built upon this variable. As Muslu et al. (2015) pointed out in the comment section of their paper, "*... similar to other studies that use computer-intensive techniques, our study is a joint test of the appropriateness of the measure and our hypotheses. Although we have included veracity checks on the measures, the validity of the empirical evidence relies on the reliability of our measures...*" In this paper, our variable of interest is the temporal focus of the information, which we define as the relative focus of future compared to past of the discussion during the earnings conference calls. Since detecting the time-reference of a sentence is a linguistic task, whether the discussion is more about the future or the past is also an observable action revealed from the contents of the earnings conference call transcripts. We want to implement out-of-sample analysis and provide a quantitative evaluation of the measurement error and consider this a first step to address the joint hypothesis issue. Supposedly, when the measurement error is low enough, our variable can capture what it's supposed to do. The reliability of the measure could potentially be disentangled with the later test of the economic hypothesis.

In order to quantify the performance of the rule-based approach, we randomly select 1,200 sentences from the corpus and manually classify each sentence into one of the five different categories. Then we compare the labels constructed by the rule-based approach against the manual ones. Table A4, Panel A presents the results. We have an overall accuracy of 0.89, meaning that out of all the predictions generated by the rule-based model, 89% are correct. Additional evaluation metrics include precision, recall, and F1-score. A precision of 0.91 for the past implies that out of 100 sentences labeled as past, 91 of them are correct. On the other hand, a recall of 0.94 suggests that out of 100 sentences with past focus, 94 are corrected labeled. The F1-score, which is the harmonic mean of precision and recall, balance both metrics and punishes approaches that optimize one at the cost of the other. Finally, the average F1-score aggregates the results for all the labels and obtains a value of 0.88. This evaluation step tells us how our rule-based method performs compared to the ground truth, and an accuracy score of 0.89 and an average F1-score of 0.88 provide strong evidence that we have a good model to identify the time-reference of the sentences.

### 4.2 Machine Learning Approach

After retrieving the quantitative evaluation metrics from the validation step, we seek to further increase the performance of identifying the time reference of sentences. Theoretically, one could go through each specific sentence and add customized rules to improve the accuracy of the rule-based algorithm. This process can be seen as a manual learning approach to refine the function that maps sentences to different time reference labels. However, such a procedure is empirically challenging to implement manually due to the potentially infinite searching set of the rules. An equally important issue is the possibility of over-fitting when more complex rules are added. Modern machine learning approaches provide a powerful set of tools to address these concerns. First, machine learning algorithms provide us with an easy way to learn the rules from the data in an automated fashion. Second, the cross-validation procedure helps to tackle the over-fitting concern.

Identifying the time reference of sentences is a standard task in supervised learning. In our case, the idea is to map each sentence into a predefined time-reference label. We firstly construct multiple features from the original sentence for such purposes. Table A3 provides an overview of the features used for training the machine learning algorithms. We include individual linguistic units (token, lemma, and pos) and their combinations (token+pos, lemma+pos). Since some of the words are strongly linked with forward-looking statements and are commonly used in the previous literature, we include them as keyword features. In addition, we calculate the cosine distance between the word vector of each individual token and the average word vector of the keyword sets. The cosine distance captures how relevant each token is related to the keyword sets. We also include bigrams (a sequence of 2 adjacent units) of tokens (lemma, pos) which provide a measure of context. As the last feature, we include the rule-based label.

For the training purpose, we rely on the manually labeled set of sentences. We divide the complete set into a training/validation set of 1,000 sentences and a test set of 2,00 sentences. We experiment with 5 different machine learning algorithms[15], i.e. Naive Bayes, Logistic Regression, Support Vector Machine, Random Forest, and XGBoost over the training/validation sample and choose the best-performing set of hyper-parameters for each algorithm. Then we evaluate the performance of each algorithm on the test set and plot the results in Figure A2. Specifically, we plot each evaluation metrics (precision, recall, and F1-score) of each method for each time reference (past, present, future, and overall).

We see that the performances of different machine learning methods are rather close to each other. The overall F1-scores are within the range of 0.8 and 0.9 and very close to the rule-based results. The overall performance of the XGBoost algorithm dominates the other methods and is slightly better than the rule-based approach. XGBoost is a tree ensemble method with gradient boosting optimization technique Chen & Guestrin (2016). Its fundamental idea is a decision tree model, which uses a set of rules generated from the input features to calculate a score that will be used to decide the label. The more advanced features come from the ensembling step (combining multiple trees) and more efficient regularization and optimization techniques. To illustrate, Figure A3 gives

[15] We use the python library scikit-learn (Pedregosa et al. (2011)) and xgboost to train the machine learning algorithms.

an example of a single decision tree from our XGBoost algorithm. We can see that a sequence of features is used to split the tree into different end-leafs. For example, the first node decides whether "rbLab:MD" is a feature, meaning it checks whether the sentence has a rule-based label of MD. Then depending on the result, it will either be assigned to a leaf value directly or will be passed to the next node, which checks whether the sentence has a feature of "pos-2-gram: MD PRP", i.e. the combination of two adjacent POS tags MD and PRP. Such an approach is essentially very similar to our rule-based method, where we use a sequence of rules derived from the tokens or POS tags to decide the time reference of the sentence. The difference is that the machine learning algorithms use a much larger set of features.

Interestingly, a natural question would be whether the algorithms can efficiently extract important features to determine the label. Our analysis also tries to shed some light on this by exploiting the rule-based label. Compared to other features, the rule-based label can be considered as a feature with concentrated pre-processed information, either from the previous literature or through the contribution of this paper. If such labels indeed have a higher information-to-noise ratio, it could reduce the searching cost of the algorithms and improve the final performance of the algorithms. Table A4 Panel B presents the results of XGBoost both with or without the rule-based label as an input feature. The result of XGBoost with the rule-based label as input outperforms the benchmark result of the rule-based approach, while the result of XGBoost without the rule-based label as input underperforms. Another critical piece of evidence comes from the feature importance ranking. Figure A4 plots the top 20 most important features from the XGBoost algorithm. The horizontal axis indicates the number of times the specific feature is used to split the data across all trees.[16] We observe that the most important feature comes from the cosine distance between individual tokens and the keywords with forward-looking meanings. This, to some extent, supports the validity of the bag of word approach widely used in the literature. Four out five of the rule-based labels appear as the important features in splitting the trees with ranks of 3rd ("rbLab:future"),

[16] `https://xgboost.readthedocs.io/en/latest/python/python_api.html`

5th ("rbLab:nan"), 7th ("rbLab:present), and 17th ("rbLab:past"). This is consistent with good performance of the rule-based approach and also explains the relatively small improvement from the machine learning method.

We provide further evidence that the rule-based approach can be considered a benchmark with good accuracy by implementing the machine learning approach. We also show that the performance of the rule-based approach could be further improved with more advanced machine learning algorithms. In the economic analysis of this paper, we rely on the results from the machine learning approach and use the rule-based approach as a robustness check. The results of the economic analysis of both methods prove to be very similar.

### 4.3 Constructing "Future minus Past" ($FMP$)

After each sentence has been classified into one of the four categories, we can construct our overall measure of temporal focus. We define "*Future minus Past*"" ($FMP_{i,t}$) for firm $i$ in quarter $t$ as the difference between the number of future-oriented sentences and past-oriented sentences, divided by the total number of sentences in the conference call.[17]

$$FMP_{i,t} = \frac{\#Sentence_{i,t}^{future} - \#Sentence_{i,t}^{past}}{\#Sentence_{i,t}} \tag{1}$$

Table 2 reports a correlation matrix of the relative future focus ($FMP$) measure, the ratio of the past-, present- and future-oriented sentences identified by the machine learning approach ($Past$, $Pre$, $Fut$), and the ratio of future-oriented sentences identified by the methods proposed from previous literature (Li (2010), Muslu et al. (2015), Bozanic et al. (2018)).[18]

- Table 2 -

[17]Note that this measure captures the polarity of past and future temporal focus and a value of zero should be interpreted as there is an equal amount of past and future information. This does not necessarily mean that the communication is present-oriented.

[18]We follow the methods from Li (2010), Muslu et al. (2015), Bozanic et al. (2018) to identify the forward-looking statements in earnings conference calls based on the descriptions and word-listed provide by their papers.

Firstly, comparing the ratio of future-oriented sentences, we observe correlations around 0.5 between the machine learning approach and the methods from the literature. Within the literature, Bozanic et al. (2018) and Muslu et al. (2015) are highly correlated while their correlations with Li (2010) are relatively lower. Overall all three variables from the literature have a correlation above 0.75. This implies that our approach of detecting the future reference is similar to existing methods, but distinct enough to contain new information.

Secondly, when we compare the $Past$, $Pre$, and $Fut$ measures, we observe a -0.31 correlation between $Fut$ and $Past$, a -0.15 correlation between $Fut$ and $Pre$, and a -0.46 correlation between $Past$ and $Pre$. This implies that the different temporal focus measures are moderately negatively correlated with each other. Thus, focusing on one time dimension only may not provide an accurate description of temporal focus.

### 4.4 Variation of $FMP$ within and across conference calls

We split the contents of the conference calls into three parts: presentation of the managers, questions of the analysts, and answers of the managers, to examine if they differ in terms of temporal focus. The corresponding variables are $FMP^P$, $FMP^A$, and $FMP^Q$, calculated with the sentences from each part. Figure 1 displays the distribution of $FMP^P$, $FMP^A$, and $FMP^Q$ with a histogram and box-plot.

First, comparing between managers' supply of information during presentation and in the answers, we observe that on average the managers are relatively more past-focused on the presentation and more future-focused on the answers. $FMP^P$ has a mean of -0.16 and $FMP^A$ has a mean of 0.04. A paired t-test shows[19] that $FMP^A$ is significantly larger than $FMP^P$ (t-value of 447). Overall, the managers indeed focus more on the past during the presentation while discussing more about the future during the Q&A session, confirming the anecdotal evidence raised in the hypothesis development and consistent with the qualitative finding of Emett (2019) for a small sample of other types

[19] For each earnings conference call, both $FMP^P$ and $FMP^A$ are constructed from the same transcript. This means that the samples of $FMP^P$ and $FMP^A$ are not independent and a paired t-test is more appropriate.

of disclosures.

Another immediate consideration is that the business nature of the firm may drive the temporal focus of the managers. We may expect to see that for firms whose future plays a larger role in its business, there will be more discussion about the future. If this is the case, we will see the distribution of $FMP$ vary across different sectors and industries.

Figure 2 plots the distribution of $FMP^P$ and $FMP^A$ among the Fama-French 48 industries (Fama & French (1997)). On the one hand, we find that pharmaceutical firms (Drugs). This makes sense since the products of these firms depend more on the future. For pharmaceutical firms, the outcomes of new medicines seem to be key to the business. On the other hand, we also see that firms in the financial sector (Banks, Fin, Insur) focus more on the past during the earnings conference calls, presumably because of regulatory constraints. Interestingly, also firms related to energy and natural resource (Coal, Oil, Mines, and Gold) focus strongly on the future, suggesting the managers do not perceive past information about commodity prices to be that relevant for the business of the firm. The results are robust to using a different industry classification, the Global Industry Classification Standard (GICS). Panel B of Table 2 shows that the differences between $FMP^P$ and $FMP^A$ hold across all industries.

## 5 Main Results

This section presents our findings regarding the market impact of $FMP$ and the discussion of the underlying economic channels. We begin by evaluating investor and analyst responses to $FMP$ (Section 5.1). Next, we analyze how $FMP$ impacts measures of uncertainty and asymmetry of information (Section 5.2). We proceed to study whether deviations from "normal" $FMP$ are related to actual future operating performance (Section 5.3). Finally, we analyze the determinants of managers' choice of $FMP$ (Section 5.4).

### 5.1 Market Reactions to Temporal Focus

The ***Communication Norm Hypothesis (H1)*** discussed in Section 2.1 posits that focusing more on the future in presentations should be perceived negatively by investors, while focusing on the future in answers should meet with a positive response by investors.

#### 5.1.1 Empirical strategy

Our empirical model for evaluating the market impact of relative future focus follows the literature on market response to earnings conference calls such as Mayew & Venkatachalam (2012), Lee (2016), Bochkay et al. (2020), Druz et al. (2020), and Suslava (2021). Specifically, in the version where we consider both presentations and answers separately we estimate:

$$\begin{aligned} CAR_{i,t} = \beta_0 &+ \beta_1 FMP^P_{i,t} + \beta_2 FMP^A_{i,t} + \beta_3 NC^P_{i,t} + \beta_4 NC^A_{i,t} \\ &+ \beta_5 SIZE_{i,t} + \beta_6 BTM_{i,t} + \beta_7 \Delta Earn_{i,t} + \beta_8 EarnSurp_{i,t} + \beta_9 RET_{i,t} + \beta_{10} VOL_{i,t} \\ &+ \beta_{11} ln(WORD^P)_{i,t} + \beta_{12} ln(WORD^A)_{i,t} + FE^{Firm}_i + FE^{YearQTR}_t + \varepsilon_{i,t}. \end{aligned} \tag{2}$$

We calculate the cumulative abnormal return ($CAR_{i,t}$) for two different time horizons. $CAR[0,1]$ captures the short-term reaction over the day of the call and the day after. $CAR[2,60]$ is calculated from the second day after the call until 60 trading dates later and captures the medium-term adjustment. By comparing the sign of the short and long-term market reaction, we can identify a drift or reversal of the stock returns and understand whether there exists under/over reaction from the investors. The daily abnormal return is calculated by adjusting the realized return with Fama-French 5 factors and the momentum factor (Carhart (1997), Fama & French (2015)).[20] We control for a range of variables that previous literature has shown affect the market response to earnings information. $SIZE_{i,t}$ is the natural logarithm of market capitalization of the

[20] In the robustness check, we also calculate the abnormal returns by applying the DGTW adjustment (Daniel et al. (1997)), the results remain very similar.

firm at the current quarter. $BTM_{i,t}$ is the natural logarithm of the book to market ratio. $VOL_{i,t}$ is the standard deviation of the daily return over the 125-days trading window prior to the earnings announcement (Collins & Kothari 1989, Mayew & Venkatachalam 2012). The fundamental information of the earnings is proxied by the standardized earnings change ($\Delta Earn_{i,t}$) and standardized earnings surprise ($EarnSurp_{i,t}$) of the current quarter following Druz et al. (2020).[21] $\Delta Earn_{i,t}$ is calculated as the difference between the earnings in the current quarter and in the same quarter of the previous year, adjusted by the volatility of the earnings changes over the past 20 quarters. $EarnSurp_{i,t}$ is calculated as the difference between the realized earnings and the consensus earnings forecasts, adjusted by the absolute value of the realized earnings.[22]

In addition, previous literature has shown that the linguistic tone of the managers during the earnings conference call significantly affects market reactions (e.g., Price et al. (2012), Brockman et al. (2015), Druz et al. (2020)). We control for tone by constructing the negativity change ($NC_{i,t}$) from the prior call using the Loughran & McDonald dictionary (Loughran & McDonald (2011)). We follow Druz et al. (2020) to use negativity change between the current and the previous quarter since innovations in negativity provide a stronger signal than the plain level measure by taking care of the company specific component.[23]

### 5.1.2 Baseline results

Table 3 reports the baseline results. Column (1) shows that call-level $FMP$ is not significantly related to the cumulative abnormal returns following the earnings conference call. However, this obscures the important distinction between $FMP$ in the presentation

[21]Both $\Delta Earn$ and $EarnSurp$ are often referred to as standardized unexpected earnings (SUE) in the literature to proxy the quantitative information from the earnings announcement. For example, $\Delta Earn$ is used in Bernard & Thomas (1989) and Tetlock et al. (2008). $EarnSurp$ is used in Mayew & Venkatachalam (2012), Lee (2016), and Bochkay et al. (2020). The major difference is that $EarnSurp$ uses the analysts' estimation as the benchmark for earnings expectation while $\Delta Earn$ uses historical earnings as the benchmark. Livnat & Mendenhall (2006) and Doyle et al. (2006) compare the two measures and find they have different effect on the returns and may capture different forms of mispricing.

[22]As a robustness check, we also replace $EarnSurp$ with $FOM$ following Chiang et al. (2019) and find similar results for our regression analysis.

[23]Using negativity changes is non-parametric and free from look-ahead bias compared to the abnormal tone measure in Huang et al. (2014).

and Q&A part.

- Table 3 -

As columns (2) to (4) show, $FMP^P$ is strongly negatively associated with $CAR[0,1]$ while $FMP^A$ has the opposite sign. The coefficients in Column (4), where both $FMP^P$ and $FMP^A$ are included, are very similar to Columns (2) and (3). This is not surprising, given that the correlation between $FMP^P$ and $FMP^A$ is only 0.2. Thus, the result of opposite signs is not mechanical.

The coefficients of $FMP^P$ and $FMP^A$ are economically sizable. For example, Column (4) implies that a one standard deviation increase in $FMP^P$ ($FMP^A$) is associated with a 20.2 (21.8) bps decrease (increase) in $CAR[0,1]$. Such economic effects of $FMP^P$ and $FMP^A$ are on the same order of magnitude as the widely researched managerial tone measures ($NC^P$ and $NC^A$).

The control variables show up with expected signs. For example, both $\Delta Earn_t$ and $EarnSurp$ are positively correlated with $CAR[0,1]$. The price momentum captured by the fiscal quarter market return, the manager sentiment captured by the negativity tone change of the transcript, and the length of the transcripts are all negatively related with $CAR[0,1]$. All the results of the control variables are consistent with previous literature.

While we control for tone changes in the conference call, one possibility is that the effect of $FMP$ comes from the tone in future- or past-referenced sentences. If in the presentation, future-oriented sentences are mostly negative and the magnitude is stronger than the past-oriented sentences, that could explain part of the negative association between $FMP^P$ and $CAR[0,1]$.

To test for this possibility, we construct the tone variables for the future- and past-referenced sentences separately. For example, to measure the negative tone in future-oriented sentences ($NegFut$), we take the difference between the number of negative and positive sentences of future-reference, divided by the total number of future-reference sentences.

$$NegFut = \frac{\#Sentences^{Future\&Negative} - \#Sentences^{Future\&Positive}}{\#Sentence^{Future}} \quad (3)$$

The tone of a sentence is defined by counting whether there are more positive or negative words from the Loughran & McDonald (2011) dictionary in the sentence. The negative tone in past-oriented sentences is constructed in a similar way. In total we have two sets of variables for each section of the presentation and Q&A, i.e. $NegFut^P$, $NegFut^A$, $NegPast^P$, $NegPast^A$.

We add the newly constructed tone measures as additional explanatory variables to Model 4 and report the estimation of the coefficients in column (5) of Table 3. We find that the coefficients for $FMP^P$ and $FMP^A$ are very stable also in this specification. Both economic and statistic magnitudes remain similar. Adding the new negative tone variables with different temporal focus does not alter the effect of $FMP$ noticeably. This implies that the effect of the relative temporal focus between the future and the past is independent of the tone of these sentences.

Is the initial reaction to future focus sustained? To test whether there exists a drift or a reversal after the two days of the event window, we regress the medium-term cumulative abnormal returns ($CAR[2, 60]$) on the same set of explanatory variables. Column (5) of table 3 reports the result. If anything, there is a slight drift for $FMP^P$; for $FMP^A$ the coefficient is positive, but completely insignificant. Overall, the initial reaction does not reverse. This suggests that the response is not an overreaction but possibly due to some more fundamental factors.

Overall, the baseline results of the market reaction provide evidence for the ***Communication Norm Hypothesis (H1)***.

#### 5.1.3 Heterogeneity in reactions: book-to-market and corporate governance

To further understand the variation of market reaction to the temporal focus, we look in the cross-section of firms and explore how the sensitivity of market reaction to $FMP$ changes with firm characteristics capturing the importance of future-oriented information as well as corporate governance.

The first test we implement is motivated by the idea that while for all firms value derives from expected future cash flows, for some firms communication about the future is particularly important because the future is likely to be different than the present. Specifically, future-oriented information can be expected to be more relevant for investors in growth firms. Thus, a higher focus on the future during the earnings conference calls potentially better satisfies the information demand of growth investors and generates a positive market reaction. Thus, we would expect the market to react more positively to $FMP$ for growth firms.

To test this hypothesis, we create a dummy variable by comparing the $BTM$ with its cross-sectional median to separate growth firms with value firms. Specifically, a $Dummy^{High}$ (in this case $BTM^{High}$) indicates that the firm's $BTM$ is higher than the median and therefore belongs to the value firm group. We interact $BTM^{High}$ with $FMP$ and run the following panel regression. If the market reaction to $FMP$ is indeed more positive for growth firms, we expect to see a negative coefficient for the interaction terms.

$$\begin{aligned}
CAR_{i,t} = \beta_0 &+ \beta_1 FMP^P_{i,t} + \beta_2 FMP^A_{i,t} + \beta_3 BTM^{High} \\
&+ FMP^P_{i,t} * \beta_4 BTM^{High} + FMA^P_{i,t} * \beta_5 BTM^{High} + \beta_6 NC^P_{i,t} + \beta_7 NC^A_{i,t} \\
&+ \beta_8 SIZE_{i,t} + \beta_9 \Delta Earn_{i,t} + \beta_{10} EarnSurp_{i,t} \\
&+ \beta_{11} RET_{i,t} + \beta_{12} VOL_{i,t} + \beta_{13} ln(WORD^P)_{i,t} + \\
&+ \beta_{14} ln(WORD^A)_{i,t} + FE^{Firm}_i + FE^{YearQTR}_t + \varepsilon_{i,t}. \qquad (4)
\end{aligned}$$

Table 4 shows the results. Column (1) shows that the interaction terms between $BTM^{High}$ and both $FMP^P$ and $FMP^A$ are significantly negative, implying that the market indeed punishes less (or rewards more) for future focus during presentations (Q&A) for growth firms. This result suggests that investors appreciate managerial focus on the future more where it actually satisfies their information demand.

The second set of tests provides first insight into the ***Managerial Tactics Hypothesis (H3)***. We use three different proxies for governance: institutional ownership, executive incentives, and manager ability. We expect that the market will give more credit to, or worry less about, unusual communication from managers of firms with good governance. We generate dummy variables to indicate whether a firm's institutional ownership, managerial incentives, and managerial ability is higher than the cross-sectional median for each of the three proxies of corporate governance. Then we interact the dummy with $FMP$ in the stock return regressions.

Columns (2)-(4) in Table 4 report the regression results. For $InstOwn$, we see a significantly positive coefficient for $FMP^A * Dummy^{High}$, indicating that investors particularly reward future focus during the Q&A for firms with high institutional ownership. For $Incentive$, we observe a significantly positive coefficient for $FMP^P * Incentive^{High}$, suggesting that investors will respond less negatively to future focus during the presentation when managers' interests are more aligned with the shareholders. For $MAscore$, both $FMP^P * MAscore^{High}$ and $FMP^A * MAscore^{High}$ are significantly positive, implying that the market will both reward more and punish less if managers are focused more on the future when they are capable. Collectively, this provides consistent evidence that the markets will consider the deviation from the norm a less severe signal when the firm has better governance.

#### 5.1.4 Analyst responses

Arguably, the main direct audience of earnings calls are the security analysts, who then convert their impressions into updated earnings forecasts. In principle, the same communication norm discussed for investors should apply to analysts as well, as per Hypothesis *H1.B (Analysts' Reactions)*. Therefore, we regress the consensus forecast change ($FC_{i,t+1}$) for the next quarter on the same set of explanatory variables as in model (4). Following Mayew & Venkatachalam (2012), we also include the $CAR[0,1]$ to control for additional information from the earnings announcement. The consensus forecast change for the next quarter ($FC_{i,t+1}$) is calculated as the difference between the post- and the pre-call consensus forecast from the analysts, adjusted by the absolute value of the actual earnings.

- Table 5 -

Table 5 summarizes the results. Column (1) shows a negative relation between $FMP$ and the consensus forecast change. A one standard deviation increase in $FMP$ is associated with a 111.3 percent decrease in the consensus forecast change next quarter ($FC_{t+1}$) relative to the magnitude of the median of $FC_{t+1}$ (-1.522/1.367=-1.113). The result is significant at the 1% level. This implies that the analysts adjust their earnings forecast downwards if the presentation of earnings conference calls focuses to a greater extent on the future.

Splitting $FMP$ by part of the call reveals that $FMP^P$ is the main driver (Columns (2) through (4)). The coefficient on $FMP^A$ is also negative (whereas Hypothesis 1.B would predict a positive relationship), but insignificant or only weakly significant. These results continue to hold when controlling for the additional tone variables (see Column (5)).

Overall, for presentations these results are consistent with *H1.B (Analysts' Reactions)* and broadly confirm the existence of a temporal focus norm also among security analysts.

### 5.2 Uncertainty, Information Asymmetry, and Heterogeneous Beliefs

We now turn to investigating whether $FMP$ affects uncertainty surrounding future earnings of the firm (*H1.C (Market Uncertainty and Information Asymmetry)*). Intuitively, a temporal focus that helps provide the additional information that meets the information demand of the audiences should be associated with lower uncertainty and information asymmetry after the earnings conference call.

To proxy for uncertainty, we use the realized daily return volatility after the earnings conference call ($VOL^{Post}$). Table 6, Column (1) reports the results from regressing $VOL^{Post}$ on $FMP^P$, $FMP^A$ and a range of control variables. The coefficients tell us that a one standard deviation increase in $FMP^P$is associated with a 1.1 percent increase in the post-call return volatility ($VOL^{Post}$), relative to the magnitude of its median (0.022/2.027=0.011). This implies that more focus on the future compared to the past in the presentation indicates an increase of the uncertainty. $FMP^A$ is not significantly related to $VOL^{Post}$.

To proxy for information asymmetry, we use the bid-ask spread. Similar to Lee (2016), we calculate the average bid-ask spread over [-3,-1] days before and [1,3] days after the call, and then use the change as the dependent variable ($\Delta Spread$). The bid-ask spread is calculated as the difference between the bid and ask price from CRSP, adjusted by the mean of the bid and ask price (Chung & Zhang (2014)). Column (2) reports that a one standard deviation increase in $FMP^P$ is associated with a 156.8 percent increase in $\Delta Spread$ relative to the magnitude of the median of $\Delta Spread$ (0.188/0.120=1.568). This suggests that focusing more on the future compared to the past in the presentation increases the information asymmetry, consistent with the communication norm hypothesis. $FMP^A$ is not significantly related to $\Delta Spread$.

As a final proxy for uncertainty we consider analyst's forecast dispersion and the consensus forecast error for the next quarter. The argument is that the level of disagreement of analysts about the future earnings reflects the difficulty in predicting earnings and a high level of disagreement also indicates higher uncertainty (Bozanic et al. (2018)). To test this hypothesis, we calculate the standard deviation of the most updated analyst estimation for each analyst in the event window [-90, 3] and [-90,-1] respectively as the post- and pre-earnings conference call analyst dispersion. We take the difference between the post- and pre-call values as the change of dispersion ($\Delta Disp$). The consensus forecast error for the next quarter ($FE_{t+1}$) is calculated as the absolute value of the difference between the actual earnings and the post-call consensus forecast from the analysts for the next quarter, adjusted by the absolute earnings of the next quarter.

Table 6, Column (3) reports the regression results for analyst dispersion. The result for the presentation is positive but not significant. For the Q&A section, a one standard deviation increase in $FMP^A$ is associated with a 95.5 percent decrease in $\Delta Disp$, relative to the magnitude of its median (-0.243/0.255=-0.955). This suggests that focusing more on the future compared to the past in the answers converges the opinions of the analysts, consistent with the communication norm hypothesis.

Looking at Column (4), the consensus forecast error is also positively related to $FMP^P$ after accounting for other controls. A one standard deviation increase in $FMP^P$

is associated with a 11.2 percent increase in the consensus forecast error ($FE_{t+1}$) relative to the magnitude of the median of $FE_{t+1}$ (1.512/13.522=0.112). This suggests that the consensus forecast will be less accurate if managers focus more on the future compared to the past in the presentation. Consistently, we also find an opposite relation between $FMP^A$ and $FE_{t+1}$.

- Table 6 -

Overall, we find strong evidence that $FMP$ increases market uncertainty and information asymmetry in the presentation but has the opposite effect in the Q&A. These results provide evidence for the ***Communication Norm Hypothesis (H1)*** and support the idea that managers' deviation from the communication norm leaves the information demand of the investors and analysts unsatisfied. These results also help rationalize the opposite directional market reactions to $FMP$ in presentations and answers since investors ask for a higher risk premium – and respond by bidding stock prices lower – when they face higher uncertainty and information asymmetry.

### 5.3 Operating Performance

So far we have focused on how the *information quantity* from $FMP$ impacts the actions of the audiences. $FMP$ may also carry specific *information content*. The negative market response to $FMP^P$ could indicate that $FMP^P$ contains negative information of the firm's economic fundamentals, as per ***H2 (Managerial Information Hypothesis)***, or suggests an agency problem, as per ***H3 (Managerial Tactics Hypothesis)***. On the other hand, the positive market response to $FMP$ during the Q&A may imply that $FMP^A$ is associated with positive information of firms' future cash-flows, as per Hypothesis 2, or a feature of good governance, as per Hypothesis 3.

We regress the future earnings change ($\Delta Earn_{i,t+1}$, $\Delta Earn_{i,t+2}$, $\Delta Earn_{i,t+3}$) of the firm on current $FMP$ and control variables.

$$
\begin{aligned}
\Delta Earn_{i,t+1} = \beta_0 &+ \beta_1 FMP^P_{i,t} + \beta_2 FMP^A_{i,t} + \beta_3 NC^P_{i,t} + \beta_4 NC^A_{i,t} \\
&+ \beta_5 SIZE_{i,t} + \beta_6 BTM_{i,t} + \beta_7 \Delta Earn_{i,t} + \beta_8 EarnSurp_{i,t} \\
&+ \beta_9 RET_{i,t} + \beta_{10} VOL_{i,t} + \beta_{11} ln(WORD^P)_{i,t} + \beta_{12} ln(WORD^A)_{i,t} \\
&+ FE^{Firm}_i + FE^{YearQTR}_t + \varepsilon_{i,t} \qquad (5)
\end{aligned}
$$

Table 7 reports the results. We observe that a one standard deviation increase in $FMP^P$ is indeed associated with a 17.09 percent decrease in the earnings change the next quarter ($\Delta Earn_{t+1}$) relative to the magnitude of the median of $\Delta Earn_{t+1}$ (0.044/0.2574=0.1709). The effect persists when looking further ahead. Since we control for contemporaneous earnings change, it is not an artifact of the well-know persistence in earnings. Thus, it appears that $FMP^P$ indeed contains negative information regarding future cash flows of the firms, which would explain the negative market reaction (as well as the reduction in earnings forecasts by analysts). In the analysis of stock price reactions, we controlled for recent performance and for linguistic tone, but the findings suggest that $FMP^P$ contains additional information.

- Table 7 -

Contrary to both Hypotheses 2 and 3, we also find a slight negative link between $FMP^A$ and future earnings. This negative relation is much smaller in magnitude and only exists in the immediate coming quarter, different from the more economically significant and persistent relation in the presentation. Still, it is striking that despite these findings for earnings, stock prices respond positively to $FMP^A$. However, stock prices are not only determined by expected future cash flows, but also discount rates. The analysis in the prior section shows that uncertainty is reduced by $FMP^A$.

Overall, the results are consistent with the notion that a future focus in presentations conveys negative fundamental information. What these results do not reveal, however, is whether this is more likely due to a direct choice of management to reveal negative information, or a consequence of the fact that agency-driven managers, who are likely to produce bad outcomes, choose to focus on the future in presentations. The results on heterogeneous stock price responses in Section 5.1.3 suggest that governance plays an important role. The next test employs the relation between $FMP^P$ and linguistic tone to provide further insights.

### 5.4 Managers' Choice of $FMP$

A specific version in which $FMP^P$ may foreshadow poor future performance is agency. Specifically, it could be that managers try to hide the negative information by focusing more on the future in presentations. Thus, instead of getting the negative signal from the content per se, the investors read through managers' tactics and interpret it as a negative sign for the firms' conditions.

For $FMP$ to be a candidate managerial tactic, it has to be related to some observable factors that might incline managers to strategically respond. To assess this possibility, we examine what drives managers' choice of $FMP^P$ and $FMP^A$ by runnning the following panel regressions:

$$\begin{aligned} FMP^P_{i,t} = {} & \beta_0 + \beta_1 NC^P_{i,t} + \beta_2 SIZE_{i,t} + \beta_3 BTM_{i,t} + \beta_4 \Delta Earn_{i,t} + \beta_5 EarnSurp_{i,t} \\ & + \beta_6 RET_{i,t} + \beta_7 VOL_{i,t} + \beta_8 \#Analysts + FE^{Firm}_i + FE^{YearQTR}_t + \varepsilon_{i,t}. \quad (6) \end{aligned}$$

$$\begin{aligned} FMP^A_{i,t} = {} & \beta_0 + \beta_1 FMP^Q_{i,t} + \beta_2 NC^A_{i,t} + \beta_3 SIZE_{i,t} + \beta_4 BTM_{i,t} + \beta_5 \Delta Earn_{i,t} + \beta_6 EarnSurp_{i,t} \\ & + \beta_7 RET_{i,t} + \beta_8 VOL_{i,t} + \beta_9 \#Analysts + FE^{Firm}_i + FE^{YearQTR}_t + \varepsilon_{i,t}. \quad (7) \end{aligned}$$

Besides the tone of the content ($NC$) and firm characteristics including size ($SIZE$), book-to-market ($BTM$), past stock return ($RET$) and volatility ($VOL$), we also include variables that reflect the earnings conditions, such as earnings change ($\Delta Earn$) and earnings surprise ($EarnSurp$) as explanatory variables. An additional consideration comes from the interactive nature of the Q&A. We expect the temporal focus of the answers ($FMP^A$) to be driven by the analysts' questions to some extent. Therefore, we also control for $FMP^Q$ when $FMP^A$ is the dependent variable.

- Table 8 -

Table 8 reports the results. The relation between the tone and $FMP$ speaks to the question whether managers choose to use future focus to communicate negative economic fundamentals of the firms directly. If so, we would expect to see a positive coefficient of $NC$, as per ***H2 (Managerial Information Hypothesis)***. However, Table 8 shows that $NC$ is strongly negatively associated with $FMP$ in both presentations and $Q\&A$, meaning that when firms talk about the future, their tone is relatively less negative. This suggests that managers tend to link future discussions with more positive tones, supporting ***H3 (Managerial Tactics Hypothesis)***.

Further support for this interpretation comes from the finding that the recent quarter's earnings change and returns have a significant negative effect on $FMP^P$, implying that firms under stress talk more about the future in the presentation.[24] This suggests that when the firm has a bad quarter, the managers either do not fully understand the reasons for the disappointing performance, or they know such negative results will persist, and therefore avoid discussing it.

Collectively, the determinants analysis results shows that managers do not reveal negative content of firm fundamentals through future focus, despite the actual negative relation between future focus and firms' future cash-flow. In addition, the fact that managers focus more on the optimistic future, especially after a bad quarter, points to the managerial incentive of avoiding discussing uncomfortable negative information.

In closing this discussion, we note that these results also suggest an additional, speculative explanation of the seemingly contradictory result that $FMP^P$ is negatively (if weakly) associated with future earnings, but positively with stock price reactions. (One explanation draws on the consequences for uncertainty, as explained above.) In particular, the results suggest that investors are more alert of managerial tactics in the presentation compared to the Q&A due to the more scripted nature of the presentation. Managers stick to scripts to avoid unintentionally revealing negative private information, and in-

[24] This relation is consistent with the result in Matsumoto et al. (2011), who find that managers use more forward-looking statements when firm performance is poor.

vestors can recognize such tactics.[25] The more interactive nature of the Q&A, where the conversations are often initiated by analysts asking questions, makes it more difficult for managers to apply managerial tactics.[26] Consequently, investors will be more vigilant of the possible agency problem in presentations than in the Q&A part. Therefore, deviation from the communication norm raises a particularly visible red flag on managers' behavior in the presentation.

Overall, these findings provide additional support for the ***Managerial Tactics Hypothesis (H3)***.

## 6 Conclusion

This paper examines the role of the relative temporal focus of information (future vs past-orientation) in the earnings conference calls. We uncover a communication norm in the earnings conference call, i.e., managers are expected to focus more on the past during the presentation, but more on the future during the Q&A. Deviation from the communication norm elicits negative reactions from the investors and analysts. Specifically, we find that the cumulative abnormal return $CAR[0,1]$ is negatively (positively) correlated with the managers' relative future focus in the presentation (Q&A). This effect is stable and is not followed by drift or reversal in the coming quarter. Analysts also adjust their earnings downwards when facing managers' deviation in the presentation. Moreover, we find that deviations increase market uncertainty, information asymmetry, diverge analysts' opinions, and increase analysts' forecast error while compliance provides the opposite effect.

We also explore the information content embedded in the temporal focus and find evidence for a managerial tactic explanation. On the one hand, we find that managers' future focus is negatively associated with future earnings, suggesting that it contains negative information about firm fundamentals. On the other hand, managers do not

[25]For example, Lee (2016) finds that investors react negatively to managers' attempts of circumventing the contemporaneity of the Q&A by adhering to predetermined language of scripted responses.

[26]Recall that column (4) of Table 8 shows that $FMP^A$ is positively associated with $FMP^Q$ with sizable economic magnitude, meaning the managers' temporal focus in the answers are strongly driven by that from the analysts' questions.

appear to directly communicate such negative information when they talk about the future. Their future focus is more associated with a positive tone. Instead, these results suggest that managers strategically focus on the future to avoid uncomfortable discussions about the bad past.

Overall, the results show that $FMP$ contains valuable information. However, investors should be, and indeed are, also mindful of the role of governance and managerial qualities in interpreting the temporal focus.

More generally, this research provides novel insight into the information conveyed in earnings conference calls. While prior work has shown, for example, that negativity in both presentations and answers has the same directional implications, the opposite directional effects for temporal focus between the presentation and Q&A is a new feature. It suggests that the information provided through these two sections, and the expectations of investors for the two sections, are different. These findings motivate further research examining the two sections separately.

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**Figure 1: Distribution of FMP in Different Sections of Earnings Conference Calls**

This figure plots the distribution of FMP in different sections of the earnings conference calls. The upper plot shows the histogram of $FMP$, $FMP^P$, $FMP^Q$. The horizontal axis indicates the value of the relative temporal focus measure, while the vertical axis indicates the number of observations. The lower plot shows the boxplots for $FMP$, $FMP^P$, and $FMP^Q$, respectively.

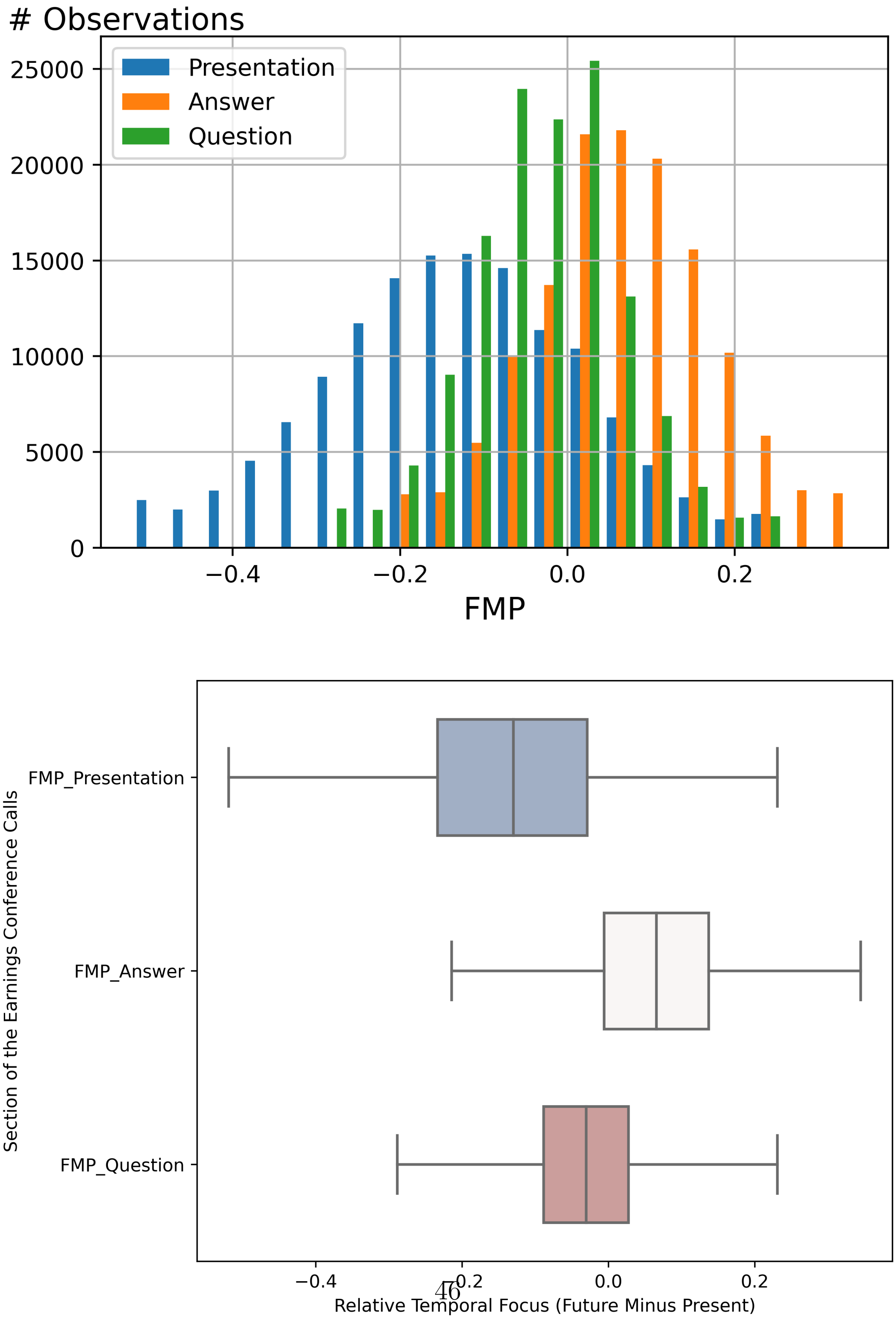

**Figure 2: Distribution of FMP across Fama-French 48 Industries**

This figure plots the box-plots of $FMP^P$ and $FMP^A$ across the Fama-French 48 industries ( Fama & French (1997)). The horizontal axis displays the relative temporal focus ($FMP$) in the presentations (left plot) and answers (right plot). The vertical axis displays the different industries sorted by the median of its corresponding $FMP$ distribution. The outliers are not displayed in the figure.

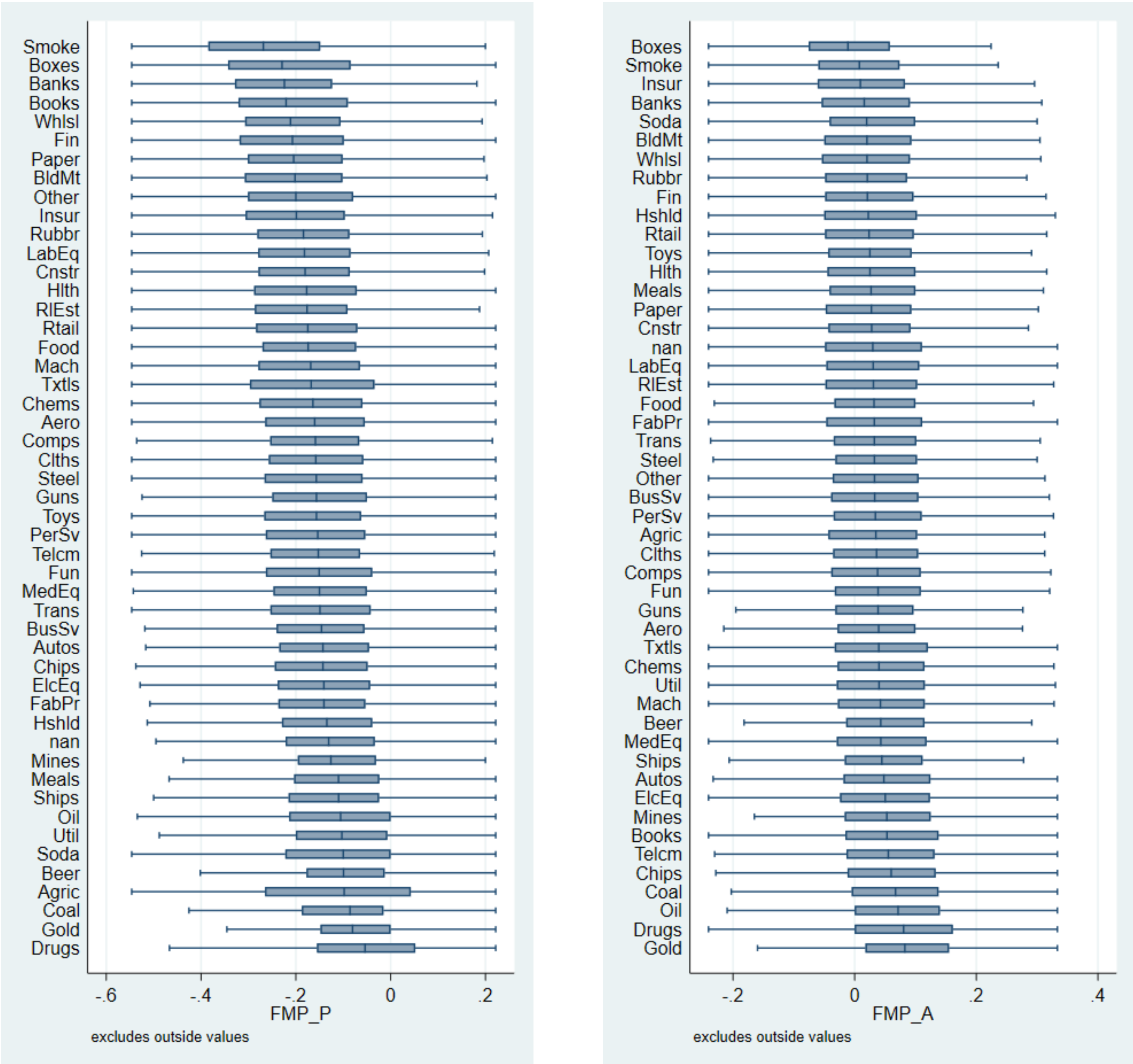

**Table 1: Sample Composition and Summary Statistics**

This table reports the sample composition and summary statistics for the variables used in the paper. Panel A and Panel B report the summary statistics for firm-level characteristics and the linguistic features of earnings conference call transcripts respectively. The definition of variables can be found at Appendix A1. Panel C and Panel D report the sector and temporal composition of the sample. The sector classification follows the global industry classification standard (GICS) obtained from the COMPUSTAT database.

**Panel A: Firm Characteristics**

| Variable | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| $SIZE$ | 157326 | 7.0910 | 1.8046 | 3.0648 | 5.8518 | 7.0194 | 8.2382 | 11.6933 |
| $BTM$ | 151562 | -0.8278 | 0.8433 | -3.4918 | -1.3087 | -0.7388 | -0.2528 | 1.0744 |
| $\Delta Earn_t$ | 129657 | 0.3301 | 1.2992 | -3.0764 | -0.3670 | 0.2623 | 1.0456 | 3.8059 |
| $\Delta Earn_{t+1}$ | 131947 | 0.3243 | 1.3052 | -3.0974 | -0.3765 | 0.2574 | 1.0427 | 3.8829 |
| $\Delta Earn_{t+2}$ | 131271 | 0.3211 | 1.3064 | -3.1002 | -0.3822 | 0.2568 | 1.0409 | 3.8786 |
| $\Delta Earn_{t+3}$ | 130270 | 0.3203 | 1.3067 | -3.1002 | -0.3839 | 0.2551 | 1.0415 | 3.8748 |
| $EarnSurp$ | 138771 | 0.0001 | 0.0128 | -0.0757 | -0.0006 | 0.0006 | 0.0024 | 0.0498 |
| $RET$ | 157240 | 0.0210 | 0.1919 | -0.5058 | -0.0781 | 0.0177 | 0.1109 | 0.7206 |
| $VOL$ | 133840 | 0.1268 | 0.0667 | 0.0397 | 0.0786 | 0.1107 | 0.1569 | 0.3777 |
| $FC_{t+1}$ | 126998 | -11.548 | 46.218 | -300.000 | -10.526 | -1.367 | 2.231 | 91.667 |
| $VOL^{Post}$ | 157285 | 2.534 | 1.752 | 0.632 | 1.391 | 2.027 | 3.062 | 10.528 |
| $\Delta Spread$ | 157109 | -0.916 | 28.418 | -137.229 | -3.699 | -0.120 | 2.461 | 131.308 |
| $\Delta Disp$ | 109904 | -0.720 | 20.534 | -104.290 | -3.132 | -0.255 | 2.150 | 94.462 |
| $FE_{t+1}$ | 126998 | 42.210 | 89.656 | 0.000 | 4.910 | 13.522 | 36.667 | 625.000 |
| $\#Analysts$ | 153201 | 9.091 | 6.778 | 1.000 | 4.000 | 7.000 | 13.000 | 32.000 |
| $InstOwn$ | 129010 | 0.661 | 0.253 | 0.004 | 0.518 | 0.727 | 0.860 | 0.991 |
| $Incentive$ | 88681 | 622.769 | 1355.678 | 1.493 | 75.595 | 206.239 | 562.954 | 10179.265 |
| $MAscore$ | 111916 | 0.001 | 0.145 | -0.232 | -0.085 | -0.034 | 0.044 | 0.566 |
| $CAR[0,1]$ | 145806 | 0.007 | 8.140 | -25.334 | -4.030 | 0.049 | 4.239 | 23.865 |
| $CAR[2,60]$ | 143430 | 0.488 | 17.003 | -52.882 | -7.822 | 0.505 | 8.618 | 56.879 |

**Panel B: Linguistic Feature of Earnings Conference Call**

| Variable | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| $FMP$ | 157360 | -0.062 | 0.090 | -0.308 | -0.119 | -0.059 | 0.000 | 0.144 |
| $FMP^P$ | 156281 | -0.157 | 0.156 | -0.547 | -0.260 | -0.154 | -0.052 | 0.222 |
| $FMP^A$ | 154610 | 0.040 | 0.112 | -0.240 | -0.034 | 0.038 | 0.113 | 0.333 |
| $FMP^Q$ | 149057 | -0.079 | 0.101 | -0.364 | -0.141 | -0.078 | -0.017 | 0.197 |
| $NC^P$ | 150822 | 0.005 | 0.332 | -0.898 | -0.188 | -0.001 | 0.192 | 0.968 |
| $NC^A$ | 147995 | 0.001 | 0.332 | -0.940 | -0.195 | 0.000 | 0.196 | 0.955 |
| $NegFut^P$ | 156202 | -0.189 | 0.166 | -0.576 | -0.300 | -0.194 | -0.083 | 0.261 |
| $NegFut^A$ | 153962 | -0.125 | 0.138 | -0.500 | -0.212 | -0.125 | -0.036 | 0.250 |
| $NegPast^P$ | 156105 | -0.106 | 0.158 | -0.500 | -0.211 | -0.108 | 0.000 | 0.303 |
| $NegPast^A$ | 153444 | -0.063 | 0.151 | -0.500 | -0.156 | -0.060 | 0.028 | 0.333 |
| $ln(WORD^P)$ | 156281 | 7.921 | 0.458 | 6.426 | 7.663 | 7.968 | 8.237 | 8.841 |
| $ln(WORD^A)$ | 154610 | 7.850 | 0.687 | 5.176 | 7.521 | 7.987 | 8.329 | 8.939 |

**Panel C: Sector Composition**

| | Sample Firms | Compustat Firms |
|---|---|---|

**Table 1 Continued**

| Sector | N | % | N | % |
|---|---|---|---|---|
| Communiaction Services | 189 | 3.82% | 835 | 3.86% |
| Consumer Discretionary | 684 | 13.81% | 2788 | 12.88% |
| Consumer Staples | 177 | 3.57% | 824 | 3.81% |
| Energy | 289 | 5.83% | 1878 | 8.68% |
| Financials | 573 | 11.57% | 3219 | 14.87% |
| Health Care | 1033 | 20.86% | 3148 | 14.54% |
| Industrials | 644 | 13.00% | 2343 | 10.82% |
| Information Technology | 1007 | 20.33% | 3564 | 16.46% |
| Materials | 208 | 4.20% | 2131 | 9.84% |
| Real Estate | 36 | 0.73% | 414 | 1.91% |
| Utilities | 108 | 2.18% | 503 | 2.32% |

**Panel D: Temporal Composition**

| | Earnings Conference Calls | | Firms | |
|---|---|---|---|---|
| Year | N | % | N | % |
| 2002 | 3061 | 1.95% | 1516 | 0.96% |
| 2003 | 6213 | 3.95% | 1910 | 1.21% |
| 2004 | 7365 | 4.68% | 2063 | 1.31% |
| 2005 | 7998 | 5.08% | 2256 | 1.43% |
| 2006 | 8465 | 5.38% | 2395 | 1.52% |
| 2007 | 8879 | 5.64% | 2522 | 1.60% |
| 2008 | 9589 | 6.09% | 2655 | 1.69% |
| 2009 | 9284 | 5.90% | 2586 | 1.64% |
| 2010 | 8900 | 5.66% | 2436 | 1.55% |
| 2011 | 8867 | 5.63% | 2412 | 1.53% |
| 2012 | 8492 | 5.40% | 2427 | 1.54% |
| 2013 | 8257 | 5.25% | 2332 | 1.48% |
| 2014 | 9168 | 5.83% | 2584 | 1.64% |
| 2015 | 9274 | 5.89% | 2645 | 1.68% |
| 2016 | 8909 | 5.66% | 2522 | 1.60% |
| 2017 | 8435 | 5.36% | 2582 | 1.64% |
| 2018 | 9521 | 6.05% | 2604 | 1.65% |
| 2019 | 9565 | 6.08% | 2616 | 1.66% |
| 2020 | 7118 | 4.52% | 2503 | 1.59% |

### Table 2: Descriptive Analysis of The Relative Temporal Focus Measure

Panel A reports the Pearson correlation between the temporal focus measure generated from our approach and the methods from the literature. Panel B reports the sample average of $FMP^P$, $FMP^A$, $FMP^Q$ across different sectors.

**Panel A: Correlation Matrix of Temporal Focus Measures**

| | $FMP$ | $Past$ | $Pre$ | $Fut$ | Li (2010) | Muslu et al. (2015) | Bozanic et al. (2018) |
|---|---|---|---|---|---|---|---|
| $FMP$ | 1.00 | -0.83 | 0.25 | 0.71 | 0.47 | 0.43 | 0.42 |
| $Past$ | -0.83 | 1.00 | -0.46 | -0.31 | -0.22 | -0.10 | -0.09 |
| $Pre$ | 0.25 | -0.46 | 1.00 | -0.15 | -0.07 | -0.18 | -0.21 |
| $Fut$ | 0.71 | -0.31 | -0.15 | 1.00 | 0.53 | 0.58 | 0.60 |
| Li (2010) | 0.47 | -0.22 | -0.07 | 0.53 | 1.00 | 0.75 | 0.82 |
| Muslu et al. (2015) | 0.43 | -0.10 | -0.18 | 0.58 | 0.75 | 1.00 | 0.91 |
| Bozanic et al. (2018) | 0.42 | -0.09 | -0.21 | 0.60 | 0.82 | 0.91 | 1.00 |

**Panel B: Sector Heterogeneity of FMP**

| Sector | $FMP^P$ | $FMP^A$ | $FMP^Q$ |
|---|---|---|---|
| Communication Services | -0.1532 | 0.0558 | -0.0762 |
| Consumer Discretionary | -0.1612 | 0.0306 | -0.0828 |
| Consumer Staples | -0.1691 | 0.0296 | -0.0775 |
| Energy | -0.1175 | 0.0706 | -0.0725 |
| Financials | -0.2268 | 0.0134 | -0.1088 |
| Health Care | -0.1114 | 0.0579 | -0.0560 |
| Industrials | -0.1685 | 0.0323 | -0.0825 |
| Information Technology | -0.1537 | 0.0440 | -0.0757 |
| Materials | -0.1667 | 0.0377 | -0.0874 |
| Real Estate | -0.1420 | 0.0490 | -0.0869 |
| Utilities | -0.1049 | 0.0423 | -0.0840 |

## Table 3: Relative Temporal Focus (FMP) and Market Reactions

This table summarizes results of panel regressions of cumulative abnormal returns on various explanatory variables. The dependent variables are $CAR[0,1]$ and $CAR[2,60]$. The explanatory variables of interest are the relative temporal focus between the future and the past in the complete transcript, the presentation, and the answers ($FMP$, $FMP^P$, $FMP^A$), and the negativity of sentences with different temporal focus in the presentation and the answer ($NegFut^P$, $NegFut^A$, $NegPast^P$, $NegPast^A$). Firm and year-quarter fixed effects are included as control variables. All continuous variables are winsorized at the 1 percent and 99 percent levels and standardized to have zero mean and unit variance. All variables are defined in Table A1. The underlying standard errors are clustered on the firm and year-quarter level. The sample period is between 2002Q1 and 2020Q4. The t-statistics are reported in parentheses below the coefficient estimates. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively.

| | (1)<br>$CAR[0,1]$ | (2)<br>$CAR[0,1]$ | (3)<br>$CAR[0,1]$ | (4)<br>$CAR[0,1]$ | (5)<br>$CAR[0,1]$ | (6)<br>$CAR[2,60]$ | (7)<br>$CAR[2,60]$ |
|---|---|---|---|---|---|---|---|
| $FMP$ | 0.002 | | | | | | |
| | (0.05) | | | | | | |
| $FMP^P$ | | -0.174*** | | -0.202*** | -0.238*** | -0.105 | -0.103 |
| | | (-5.71) | | (-6.58) | (-7.59) | (-1.43) | (-1.41) |
| $FMP^A$ | | | 0.198*** | 0.218*** | 0.200*** | 0.019 | 0.004 |
| | | | (6.86) | (7.50) | (6.81) | (0.31) | (0.07) |
| $NC^P$ | -0.875*** | -0.882*** | -0.873*** | -0.880*** | -0.676*** | -0.136** | -0.071 |
| | (-23.01) | (-23.08) | (-23.08) | (-23.13) | (-18.59) | (-2.15) | (-0.96) |
| $NC^A$ | -0.445*** | -0.444*** | -0.435*** | -0.433*** | -0.274*** | -0.049 | -0.190** |
| | (-17.64) | (-17.64) | (-17.34) | (-17.25) | (-10.41) | (-0.98) | (-2.31) |
| $NegFut^P$ | | | | | -0.114*** | | -0.155** |
| | | | | | (-3.69) | | (-2.09) |
| $NegFut^A$ | | | | | -0.195*** | | -0.102* |
| | | | | | (-6.86) | | (-1.69) |
| $NegPast^P$ | | | | | -0.658*** | | -0.086 |
| | | | | | (-16.56) | | (-1.26) |
| $NegPast^A$ | | | | | -0.461*** | | 0.035 |
| | | | | | (-14.64) | | (0.67) |
| $SIZE$ | -2.302*** | -2.303*** | -2.307*** | -2.309*** | -2.443*** | -7.506*** | -7.478*** |
| | (-14.44) | (-14.42) | (-14.49) | (-14.46) | (-15.19) | (-10.32) | (-10.18) |
| $BTM$ | 0.464*** | 0.464*** | 0.463*** | 0.464*** | 0.531*** | 0.511** | 0.534*** |
| | (6.38) | (6.41) | (6.35) | (6.38) | (7.46) | (2.64) | (2.73) |
| $\Delta Earn_t$ | 1.102*** | 1.094*** | 1.101*** | 1.091*** | 0.873*** | 0.500*** | 0.429*** |
| | (24.51) | (24.59) | (24.71) | (24.66) | (20.25) | (4.41) | (4.01) |
| $EarnSurp$ | 1.677*** | 1.677*** | 1.676*** | 1.676*** | 1.645*** | -0.017 | -0.029 |
| | (20.16) | (20.15) | (20.14) | (20.13) | (19.68) | (-0.12) | (-0.21) |
| $RET$ | -0.243*** | -0.246*** | -0.246*** | -0.251*** | -0.297*** | -0.685*** | -0.694*** |
| | (-4.55) | (-4.62) | (-4.63) | (-4.72) | (-5.53) | (-3.75) | (-3.70) |
| $VOL$ | -0.022 | -0.020 | -0.024 | -0.022 | -0.023 | 0.226 | 0.239 |
| | (-0.31) | (-0.28) | (-0.34) | (-0.31) | (-0.34) | (0.88) | (0.92) |
| $ln(WORD^P)$ | -0.229*** | -0.226*** | -0.231*** | -0.227*** | -0.168*** | -0.092 | -0.071 |
| | (-5.70) | (-5.63) | (-5.76) | (-5.68) | (-4.13) | (-1.07) | (-0.83) |
| $ln(WORD^A)$ | -0.128*** | -0.127*** | -0.116*** | -0.114** | -0.125** | 0.069 | 0.086 |
| | (-2.84) | (-2.93) | (-2.68) | (-2.63) | (-2.65) | (0.71) | (0.90) |
| $CONST$ | 0.565*** | 0.563*** | 0.566*** | 0.563*** | 0.579*** | 1.931*** | 1.938*** |
| | (16.98) | (16.89) | (16.98) | (16.88) | (16.97) | (12.23) | (11.98) |
| Firm FE | YES | YES | YES | YES | YES | YES | YES |
| YearQTR FE | YES | YES | YES | YES | YES | YES | YES |
| Std. Error Cluster | Firm, Qtr | Firm, Qtr | Firm, Qtr | Firm, Qtr | Firm, Qtr | Firm, Qtr | Firm, Qtr |
| N | 99241 | 99241 | 99241 | 99241 | 98617 | 97596 | 96982 |
| R-sq | 0.137 | 0.137 | 0.137 | 0.138 | 0.147 | 0.079 | 0.079 |

**Table 4: Growth vs Value Firms and Corporate Governance**

This table summarizes results of panel regressions of the cumulative abnormal returns on various explanatory variables, moderated by book-to-market and corporate governance measure. The dependent variable is $CAR[0,1]$. The explanatory variables of interest are the relative temporal focus between the future and the past ( $FMP^P$, $FMP^A$), the dummy variables $Dummy^{High}$ indicating whether the firm belongs to the group which is higher than the median of proxies for growth/value firm and corporate governance ($BTM$, $InstOwn$, $Incentive$, and $MAscore$), the interaction term between $FMP$ and the moderator dummy variables, the overall negativity change of the presentation and the answer ($NC^P$, $NC^A$). Firm and year-quarter fixed effects are included as control variables. All continuous variables are winsorized at the 1 percent and 99 percent levels and standardized to have zero mean and unit variance. All variables are defined in Table A1. The underlying standard errors are clustered on the firm and year-quarter level. The sample period is between 2002Q1 and 2020Q4. The t-statistics are reported in parentheses below the coefficient estimates. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively.

| | (1)<br>$CAR[0,1]$ | (2)<br>$CAR[0,1]$ | (3)<br>$CAR[0,1]$ | (4)<br>$CAR[0,1]$ |
|---|---|---|---|---|
| | $BTM$ | $InstOwn$ | $Incentive$ | $MAscore$ |
| $FMP^P$ | -0.151*** | -0.188*** | -0.338*** | -0.306*** |
| | (-3.95) | (-4.18) | (-6.94) | (-5.17) |
| $FMP^A$ | 0.324*** | 0.103** | 0.238*** | 0.215*** |
| | (7.99) | (2.23) | (4.63) | (4.46) |
| $Dummy^{High}$ | 0.494*** | 0.462*** | 0.988*** | 0.190** |
| | (5.41) | (4.31) | (12.53) | (2.31) |
| $FMP^P * Dummy^{High}$ | -0.098* | -0.010 | 0.285*** | 0.186*** |
| | (-1.97) | (-0.16) | (5.04) | (2.68) |
| $FMP^A * Dummy^{High}$ | -0.198*** | 0.208*** | 0.020 | 0.116* |
| | (-3.37) | (3.35) | (0.31) | (1.80) |
| $NC^P$ | -0.882*** | -0.837*** | -0.816*** | -0.951*** |
| | (-23.17) | (-21.60) | (-18.58) | (-21.63) |
| $NC^A$ | -0.435*** | -0.410*** | -0.414*** | -0.501*** |
| | (-17.33) | (-15.83) | (-14.40) | (-15.97) |
| $SIZE$ | -2.551*** | -2.368*** | -3.005*** | -2.451*** |
| | (-16.01) | (-13.31) | (-16.94) | (-13.19) |
| $BTM$ | | 0.528*** | 0.530*** | 0.549*** |
| | | (7.09) | (6.29) | (6.76) |
| $\Delta Earn_t$ | 1.073*** | 1.095*** | 1.028*** | 1.221*** |
| | (24.60) | (22.32) | (21.67) | (22.44) |
| $EarnSurp$ | 1.681*** | 1.685*** | 1.993*** | 1.777*** |
| | (20.11) | (19.05) | (15.16) | (16.73) |
| $RET$ | -0.265*** | -0.278*** | -0.286*** | -0.277*** |
| | (-5.02) | (-4.62) | (-4.46) | (-5.08) |
| $VOL$ | -0.039 | -0.000 | -0.021 | -0.000 |
| | (-0.55) | (-0.00) | (-0.24) | (-0.00) |
| $ln(WORD^P)$ | -0.220*** | -0.237*** | -0.229*** | -0.259*** |
| | (-5.53) | (-5.79) | (-4.50) | (-5.29) |
| $ln(WORD^A)$ | -0.111** | -0.109** | -0.229*** | -0.141** |
| | (-2.56) | (-2.38) | (-4.18) | (-2.63) |
| $CONST$ | 0.370*** | -0.350* | -0.664*** | -0.316* |
| | (6.60) | (-1.77) | (-3.70) | (-1.78) |
| Firm FE | YES | YES | YES | YES |
| YearQTR FE | YES | YES | YES | YES |
| Std. Error Cluster | Firm, Qtr | Firm, Qtr | Firm, Qtr | Firm, Qtr |
| N | 99241 | 84423 | 69033 | 73014 |
| R-sq | 0.138 | 0.146 | 0.133 | 0.139 |

**Table 5: Relative Temporal Focus (FMP) and Analyst Reactions**

This table summarizes results of panel regressions of the consensus forecast change on various explanatory variables. The dependent variables are the analysts' consensus forecast change in quarter $t+1$ ($FC_{t+1}$). The explanatory variables of interest are the relative temporal focus between the future and the past of the conference calls, presentations or answers ($FMP$, $FMP^P$, $FMP^A$). Firm and year-quarter fixed effects are included as control variables. All continuous variables are winsorized at the 1 percent and 99 percent levels and standardized to have zero mean and unit variance. All variables are defined in Table A1. The underlying standard errors are clustered on the firm and year-quarter level. The sample period is between 2002Q1 and 2020Q4. The t-statistics are reported in parentheses below the coefficient estimates. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively.

| | (1)<br>$FC_{t+1}$ | (2)<br>$FC_{t+1}$ | (3)<br>$FC_{t+1}$ | (4)<br>$FC_{t+1}$ | (5)<br>$FC_{t+1}$ |
|---|---|---|---|---|---|
| $FMP$ | -1.522*** | | | | |
| | (-6.12) | | | | |
| $FMP^P$ | | -1.460*** | | -1.433*** | -1.620*** |
| | | (-6.48) | | (-6.31) | (-6.99) |
| $FMP^A$ | | | -0.347* | -0.199 | -0.286 |
| | | | (-1.77) | (-1.01) | (-1.42) |
| $NC^P$ | -1.507*** | -1.515*** | -1.459*** | -1.516*** | -0.926*** |
| | (-7.07) | (-7.12) | (-6.90) | (-7.11) | (-4.65) |
| $NC^A$ | -0.500*** | -0.460*** | -0.480*** | -0.470*** | -0.118 |
| | (-3.42) | (-3.16) | (-3.27) | (-3.21) | (-0.74) |
| $NegFut^P$ | | | | | -1.685*** |
| | | | | | (-8.47) |
| $NegFut^A$ | | | | | -0.625*** |
| | | | | | (-3.83) |
| $NegPast^P$ | | | | | -1.269*** |
| | | | | | (-5.48) |
| $NegPast^A$ | | | | | -0.877*** |
| | | | | | (-5.05) |
| $SIZE$ | 2.013* | 1.999* | 2.016* | 2.005* | 1.741* |
| | (1.94) | (1.92) | (1.94) | (1.93) | (1.68) |
| $BTM$ | -2.826*** | -2.820*** | -2.826*** | -2.821*** | -2.670*** |
| | (-6.28) | (-6.26) | (-6.26) | (-6.26) | (-5.96) |
| $\Delta Earn_t$ | 3.197*** | 3.176*** | 3.244*** | 3.177*** | 2.639*** |
| | (10.26) | (10.15) | (10.25) | (10.14) | (8.70) |
| $EarnSurp$ | 2.736*** | 2.730*** | 2.726*** | 2.730*** | 2.675*** |
| | (6.41) | (6.38) | (6.36) | (6.38) | (5.85) |
| $RET$ | 3.386*** | 3.361*** | 3.397*** | 3.365*** | 3.206*** |
| | (12.28) | (12.17) | (12.37) | (12.15) | (11.44) |
| $VOL$ | 1.325*** | 1.333*** | 1.320** | 1.335*** | 1.327*** |
| | (2.67) | (2.69) | (2.65) | (2.69) | (2.68) |
| $ln(WORD^P)$ | -1.515*** | -1.330*** | -1.359*** | -1.328*** | -1.264*** |
| | (-6.36) | (-5.64) | (-5.70) | (-5.62) | (-5.29) |
| $ln(WORD^A)$ | -1.494*** | -1.827*** | -1.851*** | -1.839*** | -1.779*** |
| | (-6.05) | (-7.33) | (-7.32) | (-7.28) | (-6.92) |
| $CAR[0,1]$ | 8.476*** | 8.453*** | 8.484*** | 8.458*** | 8.255*** |
| | (32.47) | (32.32) | (32.54) | (32.38) | (31.85) |
| $CONST$ | -11.217*** | -11.220*** | -11.202*** | -11.220*** | -11.244*** |
| | (-36.99) | (-36.89) | (-36.74) | (-36.92) | (-36.39) |
| Firm FE | YES | YES | YES | YES | YES |
| YearQTR FE | YES | YES | YES | YES | YES |
| Std. Error Cluster | Firm, Qtr | Firm, Qtr | Firm, Qtr | Firm, Qtr | Firm, Qtr |
| N | 87147 | 87147 | 87147 | 87147 | 86725 |
| R-sq | 0.184 | 0.184 | 0.183 | 0.184 | 0.187 |

**Table 6: Relative Temporal Focus (FMP) and Uncertainty, Information Asymmetry, Difference Opinions of Analysts, and Forecast Errors**

This table summarizes results of panel regressions of uncertainty, information asymmetry, analysts' difference opinions, and analysts' forecast error on various explanatory variables. The dependent variables are the realized return volatility from 5 to 20 trading days after the earnings conference calls ($VOL^{Post}$), the change of the bid-ask spread in the 3 trading days window before and after the earnings conference calls ($\Delta Spread$), the change of analysts' forecast dispersion 3 trading days after the earnings conference calls ($\Delta Disp$), and analysts' consensus forecast error of the next quarter ($FE_{t+1}$). The explanatory variables of interest are the relative temporal focus between the future and the past in the presentation and the answers ($FMP^P$, $FMP^A$). Firm and year-quarter fixed effects are included as control variables. All continuous variables are winsorized at the 1 percent and 99 percent levels and standardized to have zero mean and unit variance. All variables are defined in Table A1. The underlying standard errors are clustered on the firm and year-quarter level. The sample period is between 2002Q1 and 2020Q4. The t-statistics are reported in parentheses below the coefficient estimates. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively.

| | (1) $VOL^{Post}$ | (2) $\Delta Spread$ | (3) $\Delta Disp$ | (4) $FE_{t+1}$ |
|---|---|---|---|---|
| $FMP^P$ | 0.022*** | 0.188** | 0.132 | 1.512*** |
| | (3.94) | (2.50) | (1.34) | (3.46) |
| $FMP^A$ | -0.006 | -0.102 | -0.243*** | -0.542* |
| | (-1.34) | (-1.37) | (-2.98) | (-1.75) |
| $NC^P$ | 0.011* | 0.285*** | -0.141 | 1.702*** |
| | (1.85) | (4.66) | (-1.55) | (5.96) |
| $NC^A$ | 0.012** | -0.054 | -0.083 | 0.506 |
| | (2.41) | (-0.72) | (-0.95) | (1.39) |
| $SIZE$ | -0.509*** | 1.115*** | 0.807* | -16.663*** |
| | (-11.23) | (3.16) | (1.96) | (-8.67) |
| $BTM$ | 0.009 | 0.295* | 0.691*** | 5.481*** |
| | (0.54) | (1.69) | (3.32) | (6.06) |
| $\|\Delta Earn\|$ | 0.044*** | -0.105 | 0.282*** | 2.026*** |
| | (6.27) | (-1.44) | (2.79) | (4.03) |
| $\|EarnSurp\|$ | 0.191*** | 0.076 | 0.933*** | 3.300*** |
| | (9.69) | (0.39) | (6.56) | (3.61) |
| $\|RET\|$ | 0.235*** | 0.189* | 0.045 | 1.320** |
| | (8.04) | (1.97) | (0.37) | (2.37) |
| $VOL$ | 0.234*** | 0.036 | -0.274 | 2.158** |
| | (8.91) | (0.24) | (-1.35) | (2.10) |
| $ln(WORD^P)$ | 0.006 | 0.026 | 0.157 | 1.552*** |
| | (0.86) | (0.26) | (1.39) | (3.05) |
| $ln(WORD^A)$ | 0.007 | -0.017 | 0.052 | -0.334 |
| | (0.90) | (-0.17) | (0.39) | (-0.58) |
| $CONST$ | 2.452*** | -0.922*** | -0.940*** | 44.891*** |
| | (255.80) | (-14.40) | (-6.40) | (76.54) |
| Firm FE | YES | YES | YES | YES |
| YearQTR FE | YES | YES | YES | YES |
| Std. Error Cluster | Firm, Qtr | Firm, Qtr | Firm, Qtr | Firm, Qtr |
| N | 104057 | 104004 | 80833 | 91354 |
| R-sq | 0.654 | 0.081 | 0.073 | 0.193 |

### Table 7: Relative Temporal Focus (FMP) and Future Operating Performance

This table summarizes results of panel regressions of the future earnings change of the firm on various explanatory variables. The dependent variables are the future earnings change of the firm in quarter $t+1$, $t+2$, and $t+3$ ($\Delta Earn_{t+1}$, $\Delta Earn_{t+1}$, and $\Delta Earn_{t+2}$). The explanatory variables of interest are the relative temporal focus between the future and the past in the presentation and the answers ($FMP^P$, $FMP^A$). Firm and year-quarter fixed effects are included as control variables. All continuous variables are winsorized at the 1 percent and 99 percent levels and standardized to have zero mean and unit variance. All variables are defined in Table A1. The underlying standard errors are clustered on the firm and year-quarter level. The sample period is between 2002Q1 and 2020Q4. The t-statistics are reported in parentheses below the coefficient estimates. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively.

| | (1)<br>$\Delta Earn_{t+1}$ | (2)<br>$\Delta Earn_{t+2}$ | (3)<br>$\Delta Earn_{t+3}$ |
|---|---|---|---|
| $FMP^P$ | -0.044*** | -0.040*** | -0.027*** |
| | (-6.95) | (-5.99) | (-4.07) |
| $FMP^A$ | -0.014** | -0.008 | 0.002 |
| | (-2.59) | (-1.56) | (0.37) |
| $NC^P$ | -0.033*** | -0.043*** | -0.084*** |
| | (-6.80) | (-7.58) | (-12.58) |
| $NC^A$ | -0.011*** | -0.015*** | -0.021*** |
| | (-2.86) | (-4.19) | (-6.02) |
| $SIZE$ | -0.062** | -0.227*** | -0.403*** |
| | (-2.49) | (-6.54) | (-8.79) |
| $BTM$ | -0.207*** | -0.222*** | -0.201*** |
| | (-16.83) | (-14.68) | (-12.32) |
| $\Delta Earn_t$ | 0.623*** | 0.387*** | 0.191*** |
| | (41.04) | (27.56) | (13.13) |
| $EarnSurp$ | -0.073*** | -0.061*** | -0.038*** |
| | (-9.22) | (-6.70) | (-4.96) |
| $RET$ | 0.093*** | 0.106*** | 0.111*** |
| | (9.11) | (11.11) | (13.57) |
| $VOL$ | -0.025* | -0.041** | -0.062*** |
| | (-1.93) | (-2.37) | (-2.97) |
| $ln(WORD^P)$ | -0.023*** | -0.016** | -0.016** |
| | (-4.20) | (-2.50) | (-2.26) |
| $ln(WORD^A)$ | -0.026*** | -0.031*** | -0.025*** |
| | (-4.58) | (-4.97) | (-3.51) |
| $CONST$ | 0.351*** | 0.381*** | 0.416*** |
| | (57.04) | (42.25) | (35.20) |
| Firm FE | YES | YES | YES |
| YearQTR FE | YES | YES | YES |
| Std. Error Cluster | Firm, Qtr | Firm, Qtr | Firm, Qtr |
| N | 103645 | 101074 | 98335 |
| R-sq | 0.425 | 0.314 | 0.263 |

**Table 8: The Determinants of Relative Temporal Focus (FMP)**

This table summarizes results of panel regressions of relative temporal focus ($FMP$) in the presentation and Q&A sessions on various explanatory variables. The dependent variables are $FMP^P$ and $FMP^A$. Firm and year-quarter fixed effects are included as control variables. All continuous variables are winsorized at the 1 percent and 99 percent levels and standardized to have zero mean and unit variance. All variables are defined in Table A1. The underlying standard errors are clustered on the firm and year-quarter level. The sample period is between 2002Q1 and 2020Q4. The t-statistics are reported in parentheses below the coefficient estimates. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively.

| | (1) $FMP^P$ | (2) $FMP^P$ | (3) $FMP^A$ | (4) $FMP^A$ |
|---|---|---|---|---|
| $FMP^Q$ | | | 2.083*** | 2.066*** |
| | | | (20.26) | (19.93) |
| $NC^P$ | | -0.532*** | | |
| | | (-10.35) | | |
| $NC^A$ | | | | -0.489*** |
| | | | | (-14.74) |
| $SIZE$ | -0.264 | -0.172 | 0.139 | 0.189 |
| | (-0.69) | (-0.45) | (0.61) | (0.83) |
| $BTM$ | 0.073 | 0.065 | 0.009 | -0.001 |
| | (0.41) | (0.36) | (0.09) | (-0.02) |
| $\Delta Earn_t$ | -0.676*** | -0.710*** | 0.046 | 0.040 |
| | (-9.89) | (-10.40) | (1.03) | (0.91) |
| $EarnSurp$ | 0.014 | -0.029 | 0.070 | 0.065 |
| | (0.27) | (-0.58) | (1.80) | (1.67) |
| $RET$ | -0.219*** | -0.281*** | 0.168*** | 0.145** |
| | (-4.34) | (-5.53) | (3.99) | (3.38) |
| $VOL$ | 0.151 | 0.149 | 0.122 | 0.130 |
| | (0.95) | (0.94) | (1.13) | (1.21) |
| $\#Analysts$ | 0.835*** | 0.795*** | 0.0327 | 0.0215 |
| | (3.77) | (3.58) | (0.26) | (0.17) |
| $CONST$ | -13.51*** | -13.51*** | 6.553*** | 6.560*** |
| | (-167.98) | (-164.94) | (139.67) | (136.36) |
| Firm FE | YES | YES | YES | YES |
| YearQTR FE | YES | YES | YES | YES |
| Std. Error Cluster | Firm, Qtr | Firm, Qtr | Firm, Qtr | Firm, Qtr |
| N | 107129 | 106226 | 104613 | 103134 |
| R-sq | 0.451 | 0.454 | 0.255 | 0.258 |

# Appendices

**Table A1: Variable Definitions**

| Variable Name | Definition |
|---|---|
| $\#Analysts$ | The number of analysts following the firm before the earnings conference call, obtained from IBES. |
| $BTM$ | The natural logarithm of the firm's book-to-market ratio (book equity divided by market capitalization) at the end of the fiscal quarter. |
| $CAR[0,1]$ | Cumulative abnormal returns in percentage on the day of the earnings conference call and the day after. The daily abnormal return is calculated by adjusting the realized return with Fama-French 5 factors and the momentum factor. |
| $CAR[2,60]$ | Cumulative abnormal returns in percentage from 2 to 60 trading days after the earnings conference call. The daily abnormal return is calculated by adjusting the realized return with Fama-French 5 factors and the momentum factor. |
| $\Delta Disp$ | The change of the standard deviation of the analysts' earnings forecast for the firm from the [-90, -1] to the [-90,3] time window relative to the date of the earnings conference call. |
| $\Delta Earn_t$ | Earnings change for quarter t. The earnings per share of the current quarter minus earnings per share of the same quarter in the previous year, adjusted by the standard deviation of the earnings change in the past 20 quarters with a minimum period of 10 quarters. |
| $EarnSurp$ | Earnings surprise. The earnings per share of the current quarter minus the analysts' consensus earnings forecast for the same quarter (the average of the most recent analysts' forecasts announced during the 90 days window before the earnings conference call), adjusted by the firm's stock price 5 days before the earnings conference call. |
| $FC_{t+1}$ | The consensus forecast change for the next quarter. The post-call consensus forecast of the analysts in the time window [-90,3] minus the pre-call consensus forecast estimation in the time window [-90,-1], adjusted by the absolute value of the actual earnings per share of that quarter, multiplied by 100. |
| $FE_{t+1}$ | The consensus forecast error for the next quarter. The absolute value of the difference between the post-call consensus forecast of the analysts in the time window [-90,3] relative to the earnings conference call for the next quarter and the actual earnings per share for the next quarter, adjusted by the absolute value of the actual earnings per share for the next quarter, multiplied by 100. |

**Table A1 Continued**

| | |
|---|---|
| $FMP$ | Future minus past, the relative temporal focus between the future and the past. The number of future-oriented sentences minus the number of past-oriented sentences, divided by the total number of sentences in the earnings conference call transcripts(presentation ($FMP^P$)/answers ($FMP^A$)/questions ($FMP^Q$)). |
| $Incentive$ | Executive incentives. A standard measure of executive incentives is "equity delta," the dollar change in executive wealth from stock and stock options per percent change of the share price, computed following Core & Guay (2002) and Coles et al. (2006). We sum delta of all disclosed executives to get a measure of the total management team's incentives. The data cover firms in ExecuComp. |
| $InstOwn$ | Institutional ownership. The total stock ownership by institutional investors relative to the number of shares outstanding, from the Thomson Reuters 13F database. |
| $MAscore$ | Managerial Ability. The managerial ability measure is defined as residual from the firm efficiency measure constructed by Demerjian et al. (2012).The data is downloaded from the website of Peter Demejian. |
| $Neg$ | Negativity. The number of negative words minus the number of positive words, divided by 1 plus the sum of negative and positive words in the earnings conference call transcripts (presentation ($Neg^P$)/answers ($Neg^A$)/questions ($Neg^Q$)). We use the word-list from Loughran & McDonald (2011) to identify the negative and positive words. |
| $NC$ | Negativity change. The difference between the negativity of current quarter and the previous quarter in the earnings conference call transcripts (presentation ($NC^P$)/answers ($NC^A$)/questions ($NC^Q$)). |
| $NegFut$ | Negativity of the future-oriented sentences. The number of negative future-oriented sentences minus the number of positive future-oriented sentences, divided by the total number of future-oriented sentences in the earnings conference call transcripts (presentation ($NegFut^P$)/answers ($NegFut^A$)/questions ($NegFut^Q$)). |
| $NegPast$ | Negativity of the past-oriented sentences. The number of negative past-referenced sentences minus the number of positive past-referenced sentences, divided by the total number of past-oriented sentences in the earnings conference call transcripts (presentation ($NegPast^P$)/answers ($NegPast^A$)/questions ($NegPast^Q$)). |
| $RET$ | Stock returns in the quarter prior to the earnings conference call. The return of the stock within the time window of 5 days after the previous earnings conference call and 5 days before the current earnings conference call. |
| $SIZE$ | The natural logarithm of the firm's market capitalization measured in millions at the end of the fiscal quarter. |
| $\Delta Spread$ | The change of the average bid-ask spread in basis points (adjusted by the mean of the bid and ask price) from the [-3,-1] time window before the earnings conference call to the [1,3] time window after the earnings conference call. |

**Table A1 Continued**

| | |
|---|---|
| $VOL$ | The monthly stock return volatility calculated as the standard deviation of the stock return in the past 48 months. |
| $VOL^{Post}$ | Post earnings conference call volatility. The realized daily return volatility calculated within the time window from 5 to 20 trading days after the earnings conference calls. |
| $ln(WORD)$ | The natural logarithm of the total number of words in the earnings conference call transcripts (presentation ($ln(WORD^{P})$)/answers ($ln(WORD^{A})$)/questions ($ln(WORD^{Q})$)). |

**Table A2: Part-of-Speech Tagging and the Temporal Focus of Information**

Panel A presents an example of the POS tagging output of NLTK for the sentence "*We achieved $1.21 billion in Digital Media revenue in Q2, a 29% increase year-over-year.*". The first and second columns present the tokens and POS tags obtained from NLTK. The third column presents the description of the POS tags. Panel B presents examples for each of the four temporal focus groups (Past, Present, Future, Undefined).

**Panel A: POS Tagging Output of NLTK**

| **Token** | **POS tag** | **Description** |
|---|---|---|
| We | PRP | Personal pronoun |
| achieved | VBD | Verb, past tense |
| $ | $ | $ |
| 1.21 | CD | Cardinal number |
| billion | CD | Cardinal number |
| in | IN | Preposition or subordinating conjunction |
| Digital | NNP | Proper noun, singular |
| Media | NNP | Proper noun, singular |
| Revenue | NN | Noun, singlar or mass |
| in | IN | Preposition or subordinating conjunction |
| Q2 | NNP | Proper noun, singular |
| , | , | , |
| a | DT | Determiner |
| 25 | CD | Cardinal number |
| % | NN | Noun, singlar or mass |
| increase | NN | Noun, singlar or mass |
| year-over-year | NN | Noun, singlar or mass |
| . | . | . |

**Panel B: Temporal Focus Categories Examples**

| **Temporal Focus** | **Example** |
|---|---|
| Past | • Q4 gross profit was $175 million, down $4 million on lower sales volumes of both golf balls and golf clubs.<br>• The Ameron acquisition added about $19.1 million in sales.<br>• Geographic revenues on an organic basis were up 28% in Asia Pacific, up 25% in the Americas and grew 18% in Europe. |
| Present | • There is no single factor that is responsible for driving the improvement.<br>• What drives – as you know, what drives the mortgage revenue is net application volume.<br>• From an investment perspective, our UK exposure is limited to $17 billion, with nearly all of those assets currency-matched with liabilities. |
| Future | • We will make sure that we have true alignment within our leadership team, and of course, the organization on our road map and our way of doing things.<br>• We're not really ready to say what the magnitude of the seasonal uptick is going to be this year.<br>• We are looking at enterprise coming back next year. |
| Undefined | • Yes, good morning.<br>• Great question, Tim.<br>• Excellent. |

**Table A3: Linguistic Features for Training the Machine Learning Algorithm**

This table lists the features used for training our machine learning model. The features are generated with python library Spacy.

| **Feature** | **Description** |
|---|---|
| Token | The tokens of the sentence. Tokens are sequences of contiguous characters grouped as useful semantic units. Examples of tokens include words, numbers, and symbols. |
| Lemma | The lemma of the tokens in the sentence. Lemmas are the canonical forms of a set of words. |
| POS | The part of speech (POS) tags of the tokens in the sentence. A part of speech (POS) is a category of words that share similar grammatical properties. |
| Token-POS | The combination of a token and its corresponding POS tag in the sentence. |
| Lemma-POS | The combination of a lemma and its corresponding POS tag in the sentence. |
| VERB_Token | The token of verbs in the sentence. |
| VERB_Lemma | The lemma of verbs in the sentence. |
| VERB_POS | The POS tags of verbs in the sentence. |
| Keywords | Whether the sentence contains forward-looking keywords such as *aim, anticipate, assume, commit, estimate, expect, forecast, foresee, hope, intend, plan, project, seek, and target.* |
| Cosine Distance | The cosine distance between the word vectors of individual word and the average word vector of the keywords. |
| Token-2-gram | The bi-gram of tokens of the sentence. Bi-grams are sequences of two adjacent language units. |
| Lemma-2-gram | The bi-gram of lemmas of the sentence. |
| POS-2-gram | The bi-gram of POS tags of the sentence. |
| Rule-based Label | The rule-based labels of the time-reference of the sentence. |

### Table A4: Rule-based Method vs Machine Learning Method

This table summarizes the validation results for the rule-based method and machine learning method. Panel A list the evaluation metrics of the rule based results against the manually labeled sample with 1200 sentences. Panel B list the evaluation metrics of the rule-based results and the XGBoost machine learning results against the test sample of 200 sentences.

**Panel A: Validation of Rule-Based Approach**

| **Rule-Based** | **Precision** | **Recall** | **F1-score** |
|---|---|---|---|
| Past | 0.88 | 0.90 | 0.89 |
| Present | 0.93 | 0.77 | 0.84 |
| Future | 0.77 | 0.95 | 0.85 |
| MD | 1.00 | 0.77 | 0.87 |
| NAN | 0.96 | 0.96 | 0.96 |
| Accuracy | | | 0.88 |
| Average | 0.89 | 0.88 | 0.88 |

**Panel B: Test Sample performance of Rule-Based Approach and Machine Learning Approach**

| **Rule-Based** | **Precision** | **Recall** | **F1-score** |
|---|---|---|---|
| Past | 0.91 | 0.94 | 0.93 |
| Present | 0.94 | 0.76 | 0.94 |
| Future | 0.81 | 0.95 | 0.87 |
| MD | 0.95 | 0.80 | 0.87 |
| NAN | 0.86 | 0.98 | 0.91 |
| Accuracy | | | 0.89 |
| Average | 0.89 | 0.89 | 0.88 |

| **XGBoost (w/o rbLabel)** | **Precision** | **Recall** | **F1-score** | **XGBoost (with rbLabel)** | **Precision** | **Recall** | **F1-score** |
|---|---|---|---|---|---|---|---|
| Past | 0.87 | 0.93 | 0.90 | Past | 0.90 | 0.97 | 0.93 |
| Present | 0.88 | 0.80 | 0.84 | Present | 0.92 | 0.79 | 0.85 |
| Future | 0.88 | 0.82 | 0.85 | Future | 0.88 | 0.91 | 0.90 |
| MD | 0.68 | 0.92 | 0.78 | MD | 0.95 | 0.80 | 0.87 |
| NAN | 0.89 | 0.95 | 0.92 | NAN | 0.86 | 0.97 | 0.91 |
| Accuracy | | | 0.87 | Accuracy | | | **0.90** |
| Average | 0.87 | 0.87 | 0.87 | Average | **0.90** | **0.90** | **0.89** |

**Figure A1: NLP Pipeline of Processing Earnings Conference Call Transcripts**

This figure plots the pipeline of processing the earnings conference call transcripts. The input is the conference call transcripts data from Refinitiv. The output consists of a table with linking identifiers to merger with CRSP, COMPUSTAT, and IBES as well as linguistic measures constructed from the transcripts data including tone and temporal focus measure.

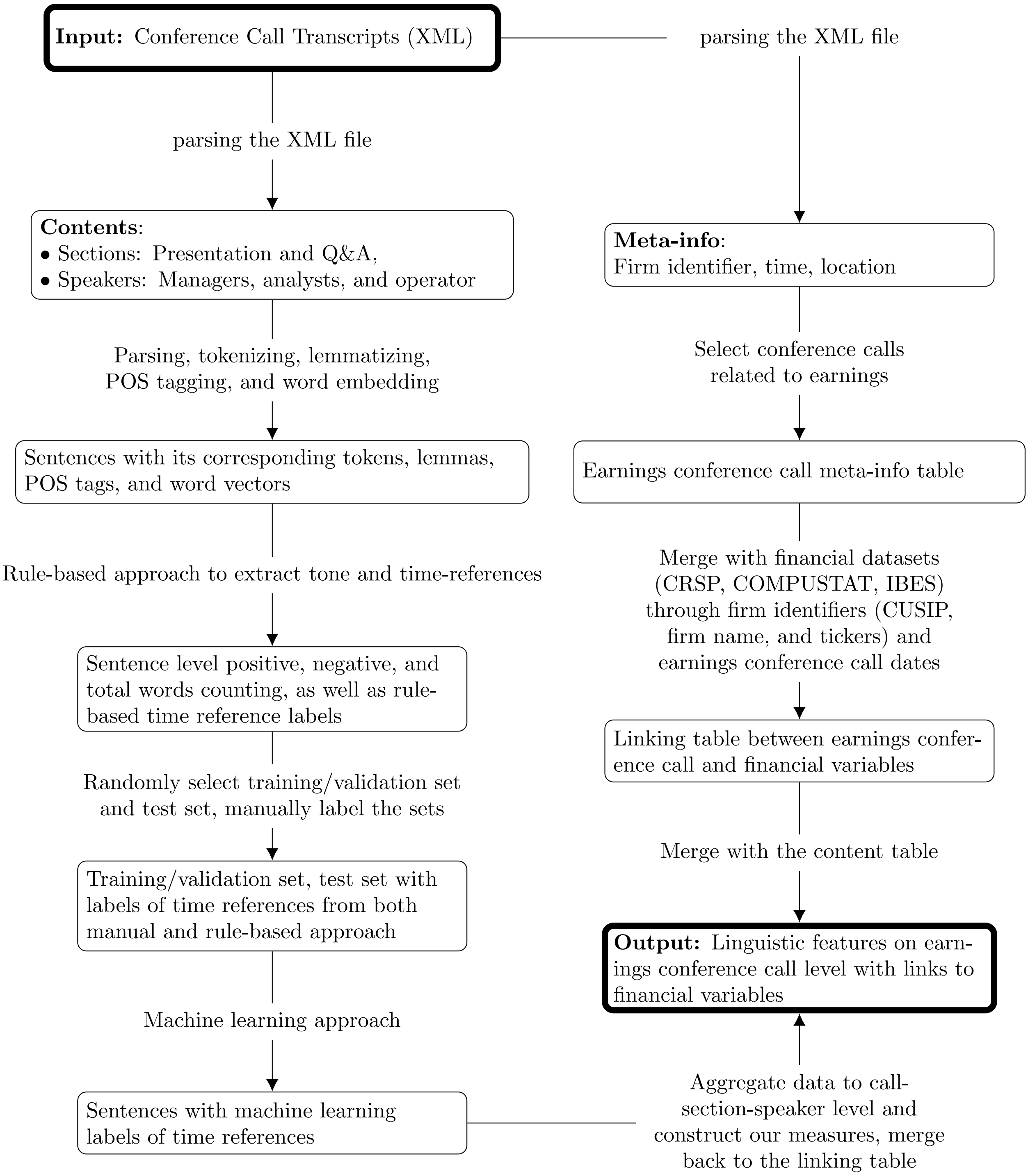

**Figure A2: Performance Comparison of Rule-Based Approach and Machine Learning Approach**

This figure plots the evaluation metrics (precision, recall, and F1-score) of each method (Naive Bayes, Logistic Regression, Support Vector Machine, Random Forest, XGBoost 1 (without rule-based label as input), XGBoost 2 (with rule-based label as input), and Rule-based method) for each time-reference (past, present, future, and overall).

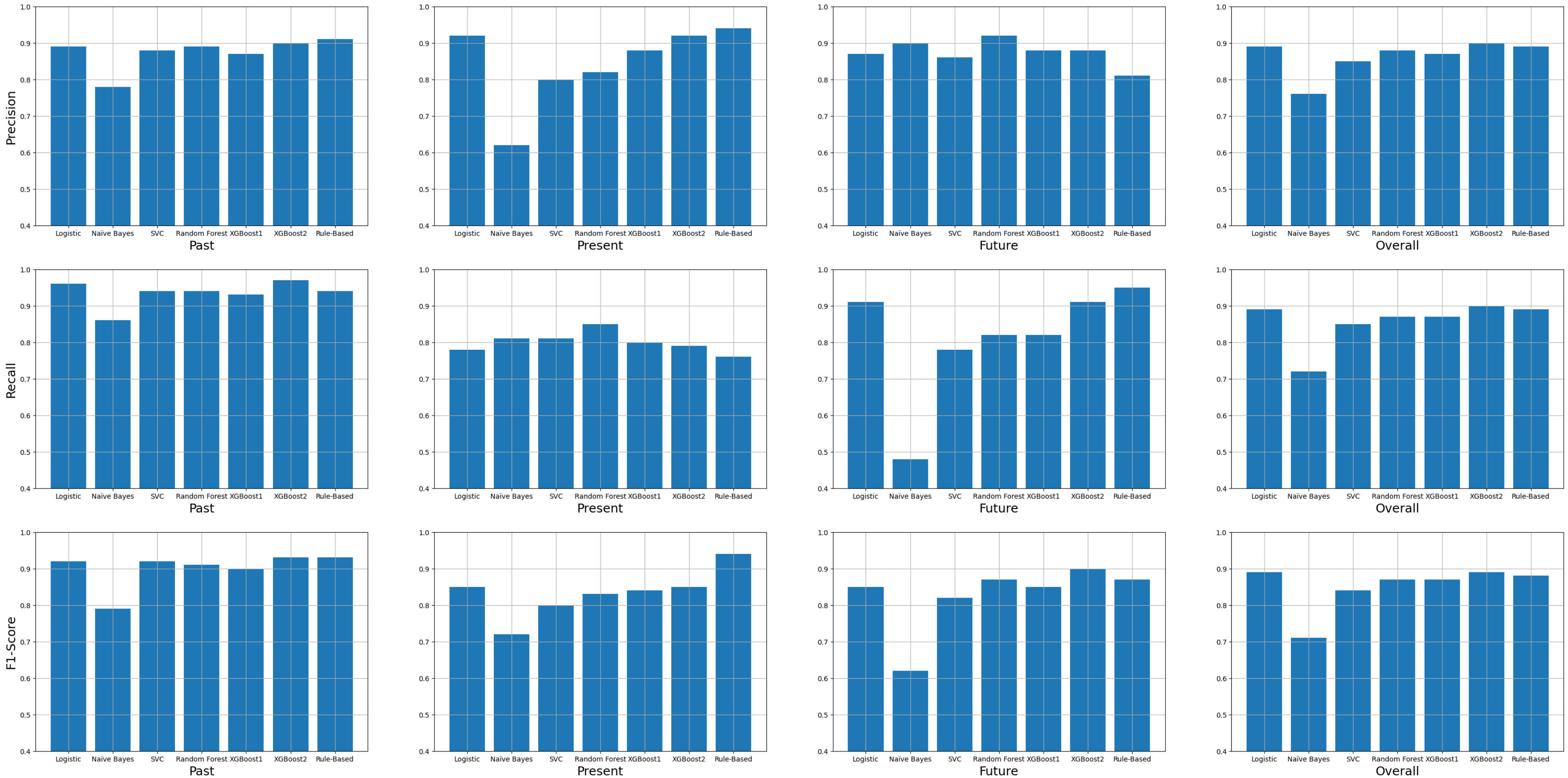

**Figure A3: Decision Tree Illustration from the XGBoost Algorithm**

This figure plots one of the decision tree inside the XGBoost algorithm. The definition of the features are in Table A3.

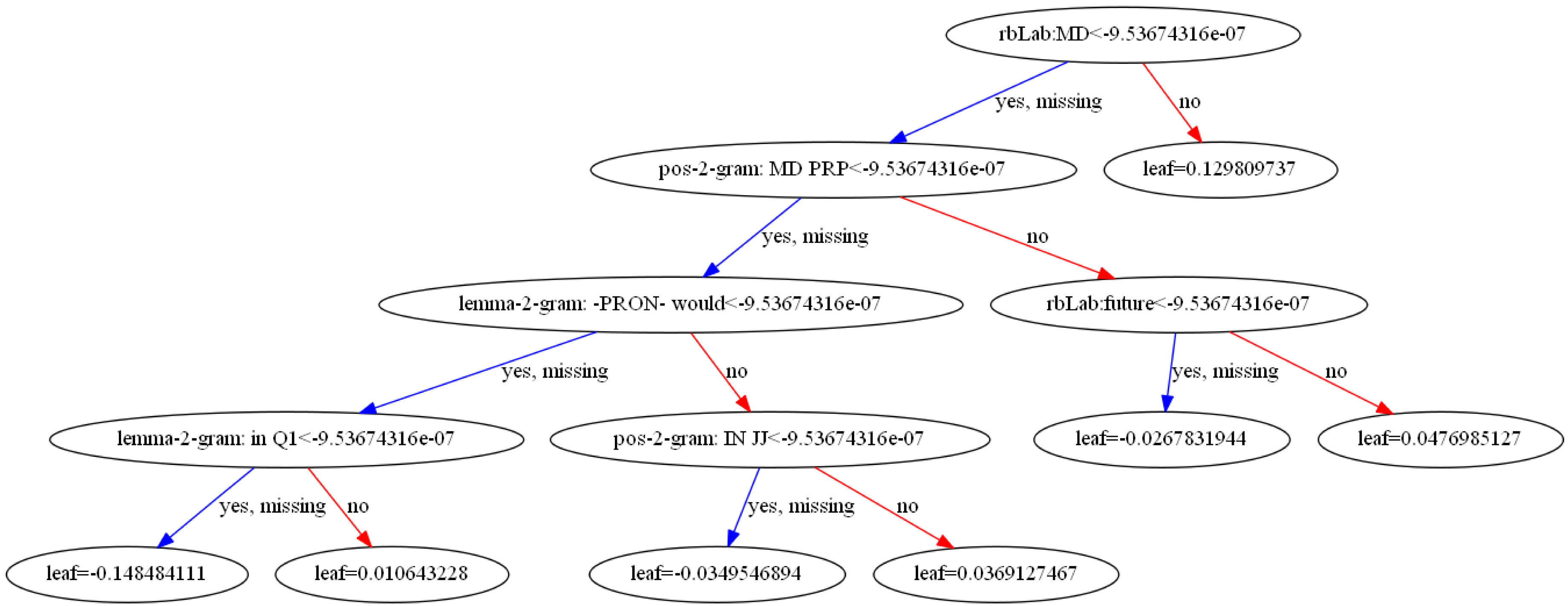

**Figure A4: Feature Importance from the XGBoost Algorithm**

This figure plots the top 20 most important features from the best performed XGBoost algorithm. The definition of the features are in Table A3. The feature importance indicates the number of times the specific feature is used to split the data across all trees.