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A Topic Modeling Perspective on Investor Uncertainty

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Abstract

We leverages computational linguistics to determine how the narrative content of earnings conference calls influences investors' uncertainty about a firm's future valuation. By applying statistical topic modeling to a corpus of 18,254 conference calls, we extract topics and tones from both analyst questions and executive responses. Our findings show that incorporating the estimated topics significantly increases the explained variance of implied volatility changes of equity options. Furthermore, our approach enables us to disentangle the overall effect into tone and topic effects, with executive statements' topics having the largest net effect, while tones from analyst statements are particularly relevant for pricing call options.

Keywords: Earnings Conference Calls, Option Implied Volatility, Natural Language Processing, Sentiment, Topic Modeling.

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1. Introduction

Quarterly earnings conference calls provide investors with valuable information affecting stock markets (Frankel et al., 1999; Brown et al., 2004; Price et al., 2012) and equity options markets (Borochin et al., 2018). While stock prices reflect a firm's current value, implied volatilities (IVs) reflect investors' uncertainty about the future valuation of a firm (Sridharan, 2015). In particular, IVs of equity options are widely used as an ex-ante measure of subjective asset price risk (Patell and Wolfson, 1979; Poterba, 1986; Canina and Figlewski, 1993). Therefore, the information disclosed during the conference call may influence investors' perception of a firm's future prospects. For example, during Apple's Q4 2021 earnings conference call, an analyst asked CEO Tim Cook about potential concerns regarding Covid-related "supply-chain headwinds". Cook responded by expressing that he was "very comfortable" with Apple's position in the chip-suppliers market. This optimistic tone was followed by an 8.9 percent decrease in the implied volatility of Apple's 60-day put option. Although Cook's remarks may have instilled confidence in Apple's ability to navigate challenging circumstances, the underlying factors driving uncertainty remains unclear.

Studies analyzing investor uncertainty perception through textual analysis of earnings conference calls often focus on sentiment analysis rather than the narrative content of the disclosure. With novel methods from statistical topic modeling, we are able to determine how the narrative content of earnings conference calls influences investors' uncertainty about a firm's future valuation. We go beyond the standard tone analysis by employing the Latent Dirichlet Allocation (LDA), a topic modeling approach from computational linguistics, to characterize the narrative content of analyst and executive statements. The LDA algorithm allows us to derive 43 generic topics for each type of participant statements. Our corpus consist of 433,022 analyst questions and 556,375 executive answers from 18,254 earnings conference calls events from companies listed in the S&P500 index. We employ implied volatilities derived from put and call options, as a proxy for investor uncertainty regarding a company's future valuation.

This paper provides new insights into the impact of conference calls on investor uncertainty. First, we contribute to the literature on voluntary disclosures by utilizing statistical computational linguistics to model topics in earnings conference calls at the statement level (i.e., individual questions and answers). We implement a methodology capable of generating interpretable topics for each type of participant statement. Second, we demonstrate that the explanatory power of the model for changes in IV substantially improves when incorporating topics from both analyst questions and executive replies, compared to a tone-only model. Moreover, our results hold across both types of options and expiration horizons, with topics from executive statements contributing to larger information gains and increasing with maturity. Third, our approach allows us to disentangle the effects of topics, tones, and controls on the average change in IV after conference calls. We show that executive statement topics have the largest net impact for options with 30, 60, and 90-day maturities, while tones from analyst statements are the dominant factor for pricing call options. Finally, we investigate the influence of topics on IV spreads, a widely recognized predictor of stock returns. Our results indicate that topics from executive statements have limited effects on volatility spreads, while those from analyst statements are insignificant. These contributions provide a distinct perspective on the impact of conference calls from statistical topic modeling and offer valuable insights for both investors' expectation formation and managers' disclosure of current results and future prospects.

The remainder of this paper is structured as follows. Section 2 reviews related literature. Section 3 presents our data. Section 4 describes our topic model and study design. Sections 5 and 6 present the main results for the change in IV and the volatility spread, respectively. Section 7 provides a note on the robustness of our results. Section 8 concludes.

2. Literature review

Corporate disclosure has been extensively studied in relation to its impact on equity markets, and to a lesser extent, on the options market. A significant area of research focuses on the impact of earnings announcements on stock returns (Ball and Brown, 1968; Beaver, 1968; Frankel et al., 1999; Brown et al., 2004; Kothari and Wasley, 2019). Ammong this vast literature[1] two notable studies stand out as the earliest to consider the impact of the tone of participants during earnings conference calls on a stock's price reaction: Price et al. (2012) and Mayew and Venkatachalam (2012). Both studies examine the relationship between abnormal stock returns and the tone of earnings releases, with Price et al. (2012) using a sentiment dictionary approach developed by Loughran and McDonald (2011) to analyze transcripts, and Mayew and Venkatachalam (2012) analyzing managers' voices. Both studies find that the overall tone of earnings conference calls is a significant predictor of cumulative abnormal returns and trade volume. These results

[1] For a comprehensive review of the literature on earnings conference calls and financial markets, see Kaya et al. (2020).

are later confirmed by Henry and Leone (2016) using different methods of measuring tones. Finally, Matsumoto et al. (2011) find that analysts' discussion sessions are more informative than managers' presentations, suggesting that investors should pay more attention to the questions and answers session rather than just the prepared remarks of the managers.

Despite its importance in modern portfolio theory, the effect of earnings announcements on the volatility of stock returns has received relatively limited attention in the literature. Prior studies on market uncertainty perception following earnings announcements have shown that IV increases before announcement days and declines afterwards (Donders et al., 2000), but the post-announcement velocity of decline depends on the content of the conference, i.e., good or bad news (Isakov and Perignon, 2001). Borochin et al. (2018) examined the contribution of managers' and analysts' tone to uncertainty perception in the stock market, as measured by option-related IV, and found a significant influence of tone measures. The study found that tones were negatively related to IV, meaning that higher negativity or pessimism increased uncertainty, and that an analyst's tone had a stronger impact on uncertainty than a manager's tone.

The importance of language in the financial domain has been widely studied in the literature[2]. Haag et al. (2019) shows that the strategic interaction between executives and financial analysts during conference calls influences the tone perception, as well as the wording and information content. Additionally, idiosyncratic factors, such as institutional ownership, can impact conference call tone (Amoozegar et al., 2020). In recent years, various natural language processing methods have been applied to finance, including support vector regressions, supervised LDA, and neural networks, among others (Frankel et al., 2017; Wujec, 2021; Hu et al., 2021).

Understanding the impact of conference calls on information asymmetry and market reactions is important for both investors and firms, and further research in this area could provide valuable insights. Prior research has shown that information asymmetry can impact stock market performance, and that conference calls can serve as a platform for firms to communicate with investors and reduce this asymmetry. Studies by Barclay et al. (1990) and French and Roll (1986) have linked stock return variances to information asymmetry, highlighting the importance of reducing information asymmetry in order to reduce stock return volatility. Earnings conference calls have been shown to play a significant role in reducing information asymmetry, with the timing and content of calls impacting the level of new

[2]For an exhaustive literature review on text analysis in finance see Loughran and McDonald (2020).

information provided (Ardia et al., 2021), and conference call characteristics being strategically used by firms to manage market expectations (Price et al., 2012).

The deviation from put-call parity theory can provide insights into the level of information asymmetry between option and stock traders, and predict future stock returns. While early studies by Klemkosky and Resnick (1979) found only small deviations, more recent research suggests that deviations are driven not only by short-sale constraints but also by better-informed traders in the options market, as argued by Cremers and Weinbaum (2010). Studies such as Doran and Krieger (2010) and Chan et al. (2015) have shown that the IV spread and skew have strong predictive power for cumulative abnormal return, and Du et al. (2018) found evidence for the predictive power of IV spread around FOMC announcements for bank stock returns. In addition, Lei et al. (2020) showed that IV spreads increase monotonically as the earnings announcement day approaches, and Atilgan (2014) found that return predictability around earnings events is stronger when volatility spreads are measured using more liquid options, in a more asymmetric information environment, and when stock liquidity is low.

3. Data

In this study, we use three types of data: earnings conference call transcripts, IV data, and controls data. We focus on firms listed in the S&P500 to ensure data completeness and enable better comparison with previous literature, including Frankel et al. (2017), Lei et al. (2020), and Borochin et al. (2018). The primary data set covers the period from the first quarter of 2006 to the second quarter of 2019. To identify series, we use a unique Reuters Instrument Code (RIC) for a specific listed company at a given conference call event. This section concludes with a brief description of the construction of our samples.

3.1. Conference call data

We collected 150,000 conference call transcripts and their metadata in HTML format from Seeking Alpha and converted them into plain text. Each transcript file includes a general information section, information on the participants of the conference calls, and the transcript of the spoken content. The general information section provides details such as the company ticker, the respective fiscal quarter, as well as the date and time of the call. The participants part of the transcript records the role of the speaking person (company's executive, referred to as executive, or analyst), their name, and position. The spoken content of the call comprises the prepared remarks section and the Q&A session. We further subdivided the content of the Q&A session into the individual statements for each participant, namely the analyst's questions and the executive's answers. Finally, we excluded transcripts dealing with firms not listed in the S&P500 index on the day of the event. Table 1 summarizes the index coverage, the number of available transcripts, and the number of questions and answers.

Table 1: Data coverage

Year	2006	2007	2008	2009	2010	2011	2012
Coverage	2.25	33.6	33.2	69	59.7	74.5	79.2
Transcripts	48	720	835	1,349	1,172	1,490	1,600
Questions	1,149	18,992	21,774	35,540	30,279	38,942	40,841
Answers	1,416	21,653	23,926	39,777	37,369	51,180	54,423
Year	2013	2014	2015	2016	2017	2018	2019
Coverage	84.3	87.2	89.6	89.4	90.7	89.9	32.4
Transcripts	1,704	1,751	1,781	1,790	1,831	1,797	386
Questions	41,461	40,190	40,533	39,715	39,050	37,150	7,406
Answers	55,097	53,521	52,391	51,948	52,963	50,683	10,028

Note: This table reports the S&P 500 index coverage in percentages, the total number of conference calls, and the total number of statements (questions and answers). Values reported in this table exclude transcripts where the corresponding options data is missing.

Our final data sample consists of 18,254 transcripts, which include 431,862 questions and 494,600 answers. The vocabulary of the questions (set of unique words for all statements) consists of 72,386 words, while the vocabulary of the answers is 115,806 words long. To ensure data quality and informative content, we exclude transcripts with a Q&A section containing less than 250 characters[3]. Table 2 presents descriptive statistics for the sample. On average, the Q&A section of the call is longer than the prepared remarks section. An average session involves around seven analysts who pose 20 questions, while three executives give an average of 25 answers. Note that some questions may receive multiple answers from different executives.

3.2. Implied volatility data

For each earnings call event, we retrieve implied volatility closing values for At-The-Money (ATM IV) call and put options on the underlying stock with 30, 60, and 90 days maturity. ATM IV values are computed following the Black Scholes option

[3]We exclude transcripts where the Q&A section is empty, as well as those that only contain non-informative statements, such as greetings or short phrases, or provide limited information, like a person's name. To filter out these transcripts, we set a minimum requirement of 250 characters for the Q&A section.

Table 2: Descriptive statistics of conference call transcripts

	Mean	Std	Min	Max
Length (in characters)	44,739.0	14,020.3	6.0	206,744.00
Length prepared remarks	18,793.5	7,282.3	0.0	161,184.0
Length Q&A	25,945.5	11,516.7	0.0	105,290.0
Number of analysts	7.2	3.8	0.0	35.0
Number of executives	3.5	1.2	0.0	18.0
Number of analyst questions	19.9	10.4	0.0	108.0
Number of executive answers	24.8	13.2	0.0	128.0

Note: This table presents summary statistics for the complete set of transcripts. Length here refers to as non-unique characters after pre-processing.

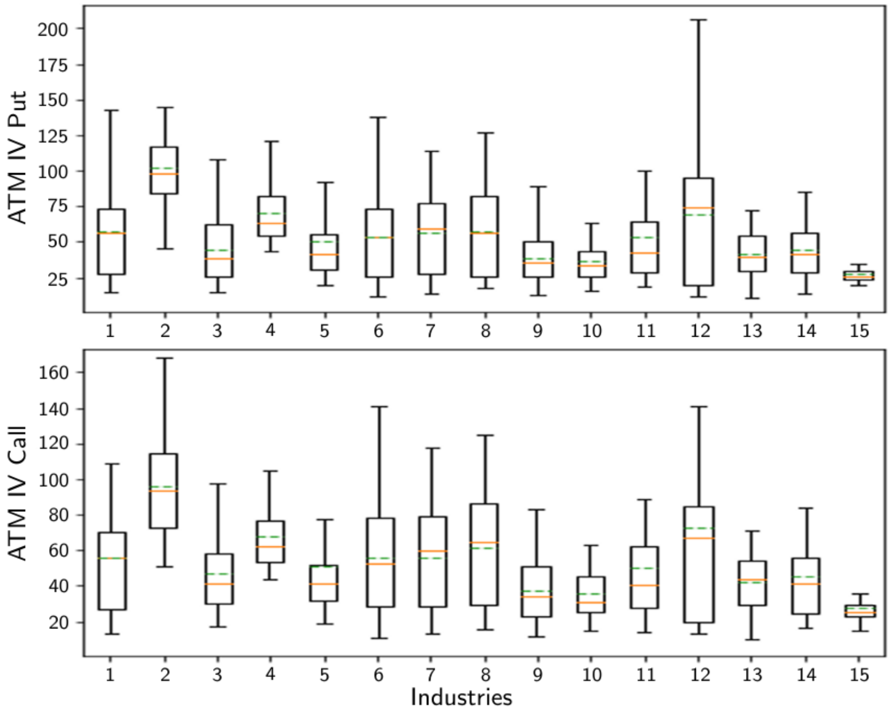
pricing model and downloaded from the Thomson Reuters database. We retrieve ATM IV closing values for the time window from one trading day before the call ($t = -1$) to five trading days after it ($t = +5$). It is important to note that the IV level is very heterogeneous across sectors represented in the index (Hann et al., 2019). Figure 1 presents the level of dispersion for ATM IV for calls and puts with 30 days maturity within and across two-digit North American Industry Classification System (NAICS) sector. The mean value and standard deviation of ATM IV are larger for puts with 30 days maturity (46.45% and 43.15%) than for calls (45.52% and 39.86%) with the same expiring date. Some sectors like finance, manufacturing, professional services, information, mining and oil, and real-state display an overall high level of volatility and intra-sectoral dispersion, however, their mean and median values differ little across instrument types.

3.3. Controls data

We complete our main data set with the inclusion of a group of series commonly used in the earnings event literature as controls for the effect of information disclosure. We divide this data into three categories namely stock prices, fundamentals, and forecast data. We retrieve the company's daily open and close stock prices on the day of the earnings call and for five trading days preceding the event. For return computation, we additionally adjust price data for stock splits and dividend payments following standard methodology (Woolridge, 1983). Specifically, we multiply all prices before the respective ex-dividend date with an adjustment factor, which is one minus the stock dividend divided by the close price one day before the ex-dividend date. Based on this data we compute the return at the conference call day ($Return$), and the five-day pre-event return ($Momentum$).

Following Fama and French (1992) and Borochin et al. (2018), we also collect fundamental data on market value and book value per share. From this information,

Figure 1: Implied volatility and industry sector



Note: This figure show the distribution of ATM IV for puts (top) and calls (bottom) with 30 days maturity, at the day of the conference event, for 15 industry sectors. The solid and dashed lines denote the median and value respectively. Industries: 1: Transportation, 2: Finance, 3: Retail trade, 4: Manufacturing, 5: Construction, 6: Professional services, 7: Information, 8: Mining and oil, 9: Wholesale trade, 10: Health care, 11: Accommodation, 12: Real Estate, 13: Utilities, 14: Administrative and support, 15: Other Services.

we derive a market value series ($Mvlog$), which is the logarithm of the firm's market capitalization on the day of the earnings event, and a book-to-market ratio series ($BmRatio$), which is the most recent book value per share divided by price.

We obtain analyst estimate data from the Institutional Brokers Estimate System (IBES) database of Thomson Reuters. Reported actual values are adjusted before entering the IBES database to match the majority accounting basis, i.e., the accounting basis used by the majority of analysts Reuters (October 2009). Based on DellaVigna and Pollet (2009) and Battalio and Mendenhall (2011), we calculate the earnings surprise ($EpsSurp$), which is the mean earnings-per-share IBES forecast less matched actual value from the earnings event covering quarter q, divided by price.

3.4. Samples construction

We combine all relevant time series data using the RIC ticker and the conference date as identifiers. The main sample is then divided into two groups: a training sample, which comprises 80% of the observations, and a test and validation sample, which consists of the remaining 20% of the observations. Table 3 summarizes the distribution of transcripts and statements in the training and test samples.

Table 3: Sample split and transcript distribution

Sample	Portion	Transcripts	Questions	Answers
Train	80%	14,719	346,651	397,644
Test	20%	3,535	85,211	96,956
Total	100%	18,254	431,862	494,600

Note: This table provides the distribution of transcripts across train and test samples.

The total count of transcripts does not include those without any content or with missing ATM IV data with a maturity of at least 30 days. These transcripts are used for the text modeling stage. In the inference step, the training sample is further refined to 13,759 observations after dropping those transcripts with incomplete data on IV at 60 or 90 days maturities, missing identifier data, or lacking control variables.

4. Research design

This study builds methodologically on the literature examining the effect of information disclosure events, such as Beechey and Wright (2009). Similar to Price et al. (2012) and Borochin et al. (2018), we consider the informativeness degree of earnings conference calls as the main source of variation on the dynamics of stock price uncertainty. Our paper, however, differs from previous literature by disentangling the effect of the content of the disclosed information from conference calls into tone and content. Additionally, we provide a scheme to approximate the latent number of recurrent topics in analyst questions and executive answers.

Our approach comprises four key steps. First, we compute the dependent variables that will serve as the main measures of stock price uncertainty (see Section 4.1). Second, we extract the key topics and tones from the content of the conference call transcripts and use the topic distribution to generate different sets of features (see Section 4.2). Third, we evaluate the performance of these different feature sets on predicting the IV-based variables (see Section 4.3). Finally, we conduct inference on the optimal feature specification, controlling for time and industry-specific effects (see Section 4.4).

4.1. Implied volatility measures

Building on the work of Borochin et al. (2018), this study employs ATM IV based dependent variables, as they offer a forward-looking measure of price uncertainty for the underlying asset. Our first variable is the log change in option ATM IV, as defined in Equation 1. Specifically, we define $\Delta option^{M}_{s,q,t+h}$ as the log change in IV of an ATM option (call or put) on stock s with maturity M (30, 60, or 90 days) on day $t = -1$ relative to the day of the year-quarter q earnings call at day $t = 0$. In addition, we examine the log change in IV up to $h = 5$ days following the conference call.

$$\Delta option^{M}_{s,q,t+h} = ln(ATM\ IV\ option^{M}_{s,q,t+h}) - ln(ATM\ IV\ option^{M}_{s,q,t-1}) \quad (1)$$

Motivated by Cremers and Weinbaum (2010), Chan et al. (2015) and Du et al. (2018), we calculate the IV spread, which has been shown to possess a strong predictive power for cumulative abnormal return (CAR). Furthermore, this variable allows us to test whether the content of earnings conference calls may influence put-call parity around earnings events. Equation 2 presents the log IV spread $spread^{M}_{s,q,t}$, which is computed as the log difference between the IV of a call and a put option for the same underlying asset s, with the same maturity M at the day of the event, i.e. $t = 0$.

$$spread^{M}_{s,q,t} = ln(ATM\ IV\ call^{M}_{s,q,t} - ATM\ IV\ put^{M}_{s,q,t}) \quad (2)$$

4.2. Topic modeling and tone extraction

In the second step of our methodology, we extract the narratives (i.e. topics) and tones from the participant statements in the Q&A section of earnings conference calls. We focus on the Q&A section because it provides a greater predictive ability for abnormal stock returns and trading volume, as reported by Price et al. (2012), and for IV, as highlighted in Borochin et al. (2018). Moreover, it enables us to concentrate on the spontaneous interaction between executives and analysts rather than on prepared statements without a reply option, which provides only marginal information gain compared to the content of the earnings press release, as suggested by Frankel et al. (2017).

4.2.1. Topic modeling

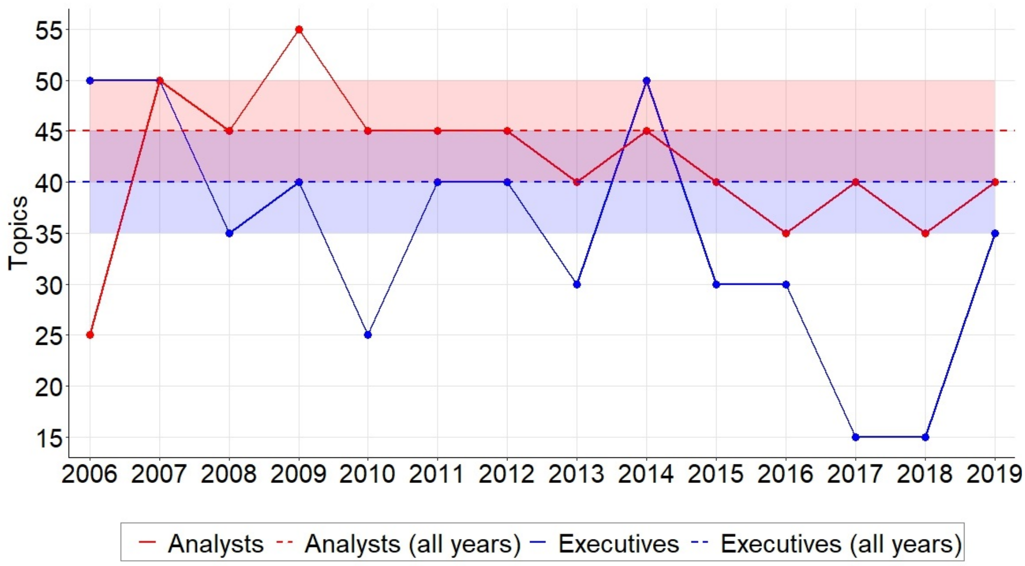
Our approach to text modeling is inspired by Bybee et al. (2020), who employ an unsupervised learning algorithm based on the LDA model proposed by Blei et al. (2003). In general, the topic model can be described as follows:

$$\check{x}^{P,k}_{s,q} = E\left[X^{P}_{s,q} \mid Z^{P}_{s,q} = z^{P}_{s,q}\right] = w\left(x^{P}_{s,q}; \underline{K}; \eta(\hat{\theta}_k)\right) \quad (3)$$

Here, $\check{x}^{P,k}_{s,q}$ represents the estimated topic weights for the participant statements P (analyst or executive) of the corresponding year-quarter q conference call transcript for company s. These topics are given for the latent distribution Z and estimated using the topic modeling function w with dis-aggregated text data (documents) x^P, which refers to the individual questions and answers.

The process w in Equation 3 summarizes a text pre-processing step and the topic model algorithm[4]. For examples of alternative NLP approaches in finance, such as the bag-of-words method, see Jegadeesh and Wu (2013), Manela and Moreira (2017), and Ardia et al. (2021). We use an $LDA(K)$ model with prior hyperparameters $\underline{K}$ and assume symmetric (uniform) priors for the document-topic distribution θ and the topic-term distribution β. Posterior inference about β and θ is drawn from the Gibbs sampling algorithm as described in Griffiths and Steyvers (2004) and implemented in R as in Hornik and Grün (2011). For further details and definitions regarding text pre-processing and topic modeling can be found in Appendix A.

Figure 2: Topics per year



Note: This Figure shows the suggested number of topics per year, given by the maximum coherence value, among the models with perplexity values below the average. Dashed lines represent median number of topics for the complete sample.

To determine the optimal prior number of topics $\underline{K}$ for our training sample, we employ a topic model evaluation strategy that considers both in-sample (co-

[4]Additional information and definitions related to the text pre-processing and topic modeling can be found in Appendix A. We also experimented with a topic modeling approach based on transformers (BERT), but the LDA model outperformed it in terms of interpretability, in-sample error, and out-of-sample error.

herence and topic intrusion) and out-of-sample (perplexity) measures, as detailed in Perico Ortiz (2022). Coherence measures the semantic similarity between high-scoring words within a set of topics, while topic intrusion is the ratio of discarded topics, due to lack of interpretability, over the prior number of topics. Perplexity is a forecast error when fitting the LDA model on an unseen chunk of documents. Appendix A.2 provides formal definitions and explanations of these measures. To identify an interval in which the optimal number of topics for each section (question and answers) may lie, we first train the model yearly with $\underline{K} = 5, 10, 15, \ldots, 100$ for each section, and then evaluate all models in a year in terms of in-sample and out-of-sample performance.[5] The suggested number of topics per year is shown in Figure 2, given by the maximum coherence value among the models with perplexity values below the year average. We define the probable region, where the true optimal number of topics for the whole sample lies, as the $+5/-5$ interval around the median coherence for the whole sample. For the analyst questions, the interval for the optimal number of topics ranges between 40 and 50, while for the manager section, the range is between 35 and 45 topics.

After identifying the optimal range of $\underline{K}$ for each section, we train the LDA model for all years in the training sample for each $\underline{K}$ value in the interval and rank the LDA specifications based on their in-and-out of sample performance. The final optimal number of topics $\underline{K} = K^*$ is also based on the performance of the resulting topics in predicting IV measures, which will be discussed in Section 4.3. We then aggregate estimated statement topic weights $\hat{\theta}_k$ at the transcript level for company s and date q using either the $\eta_1 = mean()$ or $\eta_2 = max()$ functions to match the dimensions of the dependent and control variables.

In the final step of our topic modeling we generate a set of event variables $\hat{x}^{p,k}_{s,q}$ from the aggregated topic weights, $\check{x}^{P,k}_{s,q}$, for each section P, as in Equation 4.

$$\hat{x}^{p,k}_{s,q} = \begin{cases} 1 & \text{if } \check{x}^{p,k}_{s,q} > threshold_\rho \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

This means that if the probability (here proxied by the topic weight) of a topic for a given transcript section exceeds a given value, a topic event occurs. This activation mechanism is based on the threshold ρ, computed as in Equation 5.

$$threshold_\rho = \frac{\sum_{k=1}^{K} Percentile_{\rho,k}}{K} \tag{5}$$

[5] Out-of-sample results based on the test sample described in Section 3.4.

This way of computing the threshold approximates the original frequency distribution of topics for a given sample. We calculate different sets of independent variables for ρ-values starting with 0.50 to 0.75 in 0.05 steps.

The resulting features are well-suited to our study design because they allow us to interpret the impact of these variables on our targets as the effect of a question or answer event related to a particular topic. While we also considered using the aggregate topic weights directly without a threshold ($threshold = none$), this approach would imply that the effect of these features on our dependent variables is a percentage increase in the quasi-probability that a question or answer relates to a specific topic.[6]

4.2.2. Tone extraction

We adopt the finance-specific dictionary of Loughran and McDonald (2011) to determine the tone values of analyst and executive statements. The dictionary classifies a set of 50,115 words that appear in 10-Ks according to their financial sentiment, i.e., positivity or negativity. We compute separate tone scores for different sections of the call transcript to account for various aspects of the call. Specifically, we follow Price et al. (2012) to derive tone scores for the prepared remarks section, which primarily reiterates the earnings press release. We also extract tone scores for the Q&A session, as well as for the first and second halves of analyst statements within this session, following the approach of Mayew (2008) and Cen et al. (2021). To summarize, Table 4 presents the estimated tone variables based on our transcripts data set.

Table 4: Descriptive statistics tone variables

	Mean	Std	Min	Max
Q&A tone	-0.4414	0.5935	-1.0000	1.0000
Analysts tone	-0.0005	0.0077	-0.0909	0.0909
Executives tone	0.0071	0.0074	-0.1667	0.1667
First analyst tone	-0.3129	0.4621	-1.0000	1.0000
Last analyst tone	-0.3429	0.4576	-1.0000	1.0000

Note: This table provides summary statistics for tone variables based on Loughran and McDonald (2011) methodology. Negative values imply a negative tone.

Our estimated tone variables are consistent with previous studies, such as Borochin et al. (2018). We find that the Q&A section exhibits a negative tone, largely driven by the negative tone of the analysts' questions. Conversely, executives' answers tend

[6]Topic weights are not coerced to sum up to one.

to have a positive tone when responding to analyst questions. Interestingly, we observe that the initial questions asked by the analysts tend to have a less negative tone than the questions asked later in the session.

4.3. Dimensionality reduction and model selection

In order to deal with the high dimensionality of our datasets in terms of the number of topic variables, we employ a penalized regression approach based on the Least Absolute Shrinkage Selection Operator (LASSO), as described in Larsen et al. (2021). This approach has two goals: First, obtain sparse coefficient specifications; second, recover both in-sample and out-of-sample model performance metrics for selecting the baseline models for analyst questions and executive answers.

To this end, we run the penalized regression separately for each combination of statement type (questions or answers), posterior number of topics K, aggregation function η, and threshold value ρ on the complete set of dependent variables ($\Delta option^M s, q, t$ and $spread^M s, q, t$) at each maturity horizon $M = 30, 60, 90$. We also include the full set of controls in the LASSO estimation, but exclude tone variables. To obtain the optimal level of penalization λ^*, we use a 5-split time series cross-validation[7]. We calculate the in-sample and out-of-sample Mean Square Error (MSE) and the Akaike information criterion (AIC) for each specification.

We then select the best model for each type of statement by ranking specifications in terms of their predictive performance with respect to volatility measures, as well as their text model performance in terms of interpretability (coherence) and predictability (perplexity). We refer to these rankings as the *feature model ranking* and *text model rankings*, respectively. The *feature model ranking* is based on the in-sample and out-of-sample metrics obtained during the cross-validation step for each dependent variable and each maturity level. Since we are interested in estimating the effect of the same set of topics at different maturities, we assign a higher ranking weight (50%) to short-term maturities (30 days) and lower weights to 60 days (30%) and 90 days (20%) within the feature ranking. The *text model ranking* is described in Section 4.2.1.

We assign equal weights to the feature-model and text-model rankings when computing the *overall model ranking*. Based on this approach, we find that the optimal LDA specification includes 43 topics ($K = 43$), an aggregation function using the max function ($\eta = \max$), and a threshold of 0.5 ($\rho = 0.5$) for both analyst questions and executive answers. Appendix B provides a description of the top three

[7] It is a variation of the k-fold cross validation method, in which successive training sets are supersets of those that come in the previous fold.

keywords from the optimal LDA specification for analyst questions (Table B.2) and executive answers (Table B.3). For further details on model selection, please see Appendix A.4.

4.4. Statistical inference

We employ a two-stage regression approach to estimate the impact of text-based variables on IV measures, summarized in Equation 6. In the first stage, we conduct LASSO regressions on the best-ranked topic specifications, $\hat{x}^{p,k}_{s,q}$, for each volatility measure $y^{M}_{s,q,t+h}$ and each type of statement p. We exclude controls and tones to obtain a sparse topic specification that consists of K^* number of topics. In the second stage, we estimate a time- and fixed-effect panel model on the topic-sparse specification that includes a vector of tone variables *tone* and a vector of controls c, which includes returns, forecasts, fundamentals, and conference-specific data,

$$y^{M}_{s,q,t+h} = \alpha + \sum_{k=1}^{K^*} \beta_k x^{p}_{k,s,q} + \sum_{p=1}^{P} \psi_p tone_{p,s,q} + \sum_{c=1}^{C} \gamma_c c_{c,s,q} + \delta_{time} + \nu_{entity} + \epsilon_{s,q,t+h} \quad (6)$$

where y refers to a volatility measure ($\Delta option^{M}_{s,q,t+h}$, $spread^{M}_{s,q,t+h}$), p denotes the participant (either analyst or executive), δ_{time} represents year time effects (12 periods), and ν_{entity} stands for 2-digit NAICS industry level fixed effects (15 entities). The index h indicates the estimation horizon relative to the conference day, $t = 0$. We estimate Equation 6 using standard panel OLS with cluster-robust standard errors to account for heteroskedasticity and autocorrelation in the residuals.

5. Effect of analysts and executives statements on implied volatility

This section presents the effects of estimated topics from conference call transcripts on the firm's future valuation uncertainty, measured by a stock's implied options volatility. We divide these results in three parts: The first one examines the effect of analyst questions on IV (Section 5.1), while the second one focuses on executive statements (Section 5.2). We conclude with an examination of post-event dynamics and component contribution (Section 5.3).

Before we examine the effect of each type of participant statements, we present results for the baseline specification, which include only the full set of controls and tone variables. These regressions are estimated as in Equation 6 using the change in implied volatility for puts and calls with 30 days maturities from one day before the conference call event to the event day as dependent variable. This specification serves two goals: First it allows to validate the sign and significance level of tones and controls with respect to previous studies. Second, it serves as a benchmark for the effect of topic variables on IV. Table 5 summarizes the results for the baseline specification.

Table 5: Puts and calls with 30 days maturity, control variables and tones

	$ln\Delta Put^{30}$				$ln\Delta Call^{30}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Const	-0.1522	-0.2074	-0.1657	-0.2257	-0.1403	-0.1998	-0.1665	-0.2302
	(0.1022)	(0.1085)*	(0.0940)*	(0.0941)*	(0.1005)	(0.1126)*	(0.0939)*	(0.0985)**
Return	0.1136	0.0964	0.1221	0.1058	0.1667	0.1503	0.1776	0.1620
	(0.0346)***	(0.0322)***	(0.0352)***	(0.0353)	(0.0322)**	(0.0494)***	(0.0487)***	(0.0469)***
Momentum	-0.3098	-0.3191	-0.3037	-0.3129	-0.3515	-0.3604	-0.3455	-0.3543
	(0.0426)***	(0.0389)***	(0.0404)***	(0.0376)***	(0.0447)***	(0.0401)***	(0.0426)***	(0.0389)***
BmRatio	0.0102	0.0078	0.0044	0.0010	0.0097	0.0070	0.0066	0.0029
	(0.0116)	(0.0106)	(0.0097)	(0.0086)	(0.0110)	(0.0100)	(0.0078)	(0.0068)
EpsSurp	0.0126	0.0023	-0.0021	-0.0401	-0.0138	-0.0189	-0.0505	-0.0585
	(0.0376)	(0.0339)	(0.0439)	(0.0392)	(0.0357)	(0.0310)	(0.0433)	(0.0401)
Mvlog	0.0063	0.0123	0.0065	0.0131	0.0049	0.0113	0.0063	0.0131
	(0.0095)	(0.0102)	(0.0085)	(0.0093)	(0.0102)	(0.0108)	(0.0087)	(0.0093)
AnaTone	-0.9195	-0.5133	-0.8502	-0.4374	-1.1913	-0.7678	-1.1223	-0.6975
	(0.4139)**	(0.3640)	(0.4497)*	(0.4024)	(0.3627)**	(0.3474)**	(0.3821)**	(0.3528)**
ExeTone	-1.0496	-0.9091	-0.7441	-0.5646	-0.9659	-0.7966	-0.7085	-0.4966
	(0.5220)**	(0.5595)	(0.3555)**	(0.3883)	(0.4685)**	(0.4848)	(0.3157)**	(0.3200)
AnaQues	0.0000	-0.0005	0.0002	0.0002	0.0002	-0.0002	0.0005	0.0001
	(0.0000)	(0.0003)	(0.0003)	(0.003)	(0.003)	(0.0003)	(0.0003)**	(0.0003)
ExeAns	-0.0003	-0.0002	-0.0002	-0.0001	-0.0006	-0.0004	-0.0004	-0.0002
	(0.0002)*	(0.0002)	(0.0002)	(0.0001)	(0.0002)***	(0.0002)**	(0.0002)**	(0.0002)
Effects	none	time	ind.	time ind.	none	time	ind.	time ind.
Obs	13759	13759	13759	13759	13759	13759	13759	13759
Adj. R^2	0.0250	0.0233	0.0236	0.0216	0.0283	0.0267	0.0273	0.0254

Notes: $ln\Delta Put^{30}$ and $ln\Delta Call^{30}$ denotes the log of the contemporaneous change in ATM IV for puts and calls with 30 days maturities respectively. Clustered standard errors. *, **, and *** indicate significance at the 10%, 5% and 1% critical level, respectively.

Return variables, given by the daily return (*Return*), the pre-event return (*Momentum*), and the tones appear to be the main control variables for the contemporaneous change in the IV for both types of options. These results are robust to time and industry fixed effects. Tone values have the expected negative sign as in Borochin et al. (2018). An increase of 0.1 points in executive tone reduces the volatility of puts by 1.0496 *percentage points* (*pp.*) for puts and 0.9659 *pp.* for calls. These effects are robust to industry effects but not to time effects. Only Analysts tone is significant and robust to time and fixed effects for calls IV. There is weak evidence that an increase in the number of executive answers reduces volatility of calls options.

5.1. Implied volatility and analyst questions

This section looks at the impact of topic variables derived from analyst questions on investor's perceived uncertainty about future valuations, as expressed by the log change in the IV of options with a 30-day maturity. Appendix B contains additional results for maturities of 60 and 90 days. The topics[8] in this section are generated using the LDA algorithm with the best overall ranked parametrization ($\underline{K} = 43$, $\eta = max()$, and $\rho = 0.5$), as described in Section 4.3. Table 6 shows the regression results for the contemporaneous change in IV for calls (1-4) and puts (5-8) with 30-day maturity. The LASSO filter was used to determine the sets of topic variables in each regression. Due to space limitations, we only report the top ten topics in the table. For a complete list of topics and their effect on all available maturity horizons, see Table B.2 in the appendix.

Table 6: Puts and calls with 30 days maturity, selected topics from analyst questions and tones

	$ln\Delta Put^{30}$			$ln\Delta Call^{30}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Const	-0.139	-0.155	-0.221	-0.125	-0.141	-0.227
	(0.101)	(0.100)	(0.099)**	(0.107)	(0.105)	(0.098)**
topic 6	-0.012	-0.012	-0.007	-0.013	-0.012	-0.007
cost expense target	(0.005)***	(0.005)**	(0.004)**	(0.004)***	(0.004)***	(0.004)*
topic 12	0.018	0.019	0.023	0.02	0.021	0.026
global market supply	(0.007)***	(0.006)***	(0.006)***	(0.004)***	(0.004)***	(0.004)***
topic 13	0.029	0.031	0.024	0.031	0.033	0.027
unit confidence visibility	(0.018)	(0.018)*	(0.019)	(0.011)***	(0.01)***	(0.012)**
topic 17	-0.000	-0.003	-0.003	0.012	0.008	0.013
capital risk loss	(0.007)	(0.006)	(0.019)	(0.006)*	(0.005)	(0.004)***
topic 18	-0.063	-0.059	-0.046	-0.064	-0.06	-0.047
retail consumer store	(0.028)**	(0.028)**	(0.029)	(0.025)**	(0.026)**	(0.027)*
topic 25	0.036	0.038	0.026	0.036	0.037	0.026
new plattform booking	(0.012)***	(0.012)***	(0.006)***	(0.012)***	(0.013)***	(0.006)***
topic 29				-0.05	-0.05	-0.039
level inventory industry				(0.006)***	(0.006)***	(0.008)***
topic 32	-0.04	-0.037	-0.034	-0.04	-0.037	-0.033
margin segment improvement	(0.011)***	(0.01)***	(0.011)***	(0.008)***	(0.007)***	(0.008)***
topic 35	-0.037	-0.037	-0.024	-0.033	-0.033	-0.02
pricing volume gross_margin	(0.007)***	(0.007)***	(0.004)***	(0.006)***	(0.006)***	(0.005)***
topic 42				0.056	0.055	0.038
increase capacity rate				(0.029)*	(0.028)*	(0.022)*
$AnaTone$		-0.874	-0.406		-1.129	-0.634
		(0.382)**	0.383		(0.331)***	(0.335)*
$ExeTone$		-0.931	-0.497		-0.806	-0.394
		(0.53)*	0.422		(0.456)*	0.328
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs	13759	13759	13759	13759	13759	13759
Adj. R^2	0.032	0.036	0.032	0.035	0.039	0.035
Effects	none	none	time+ind	none	time	time+ind

Note: $ln\Delta Put^{30}$ and $ln\Delta Call^{30}$ denotes the log of the contemporaneous change in ATM IV for puts and calls with 30 days maturities respectively. Clustered standard errors. *, **, and *** indicate significance at the 10%, 5% and 1% critical level, respectively.

The estimated topics in Table 6 are interpretable, and the majority of them

[8] Topic labels are formed by an arbitrary combination of three keywords within the top ten keywords such that they can be easily interpreted.

show the expected signs. For example, after controlling for time effects and industry heterogeneity, analyst statements about market supply conditions *topic 12* increase IV by around 0.018 *pp.* for puts in (1) and 0.02 *pp.* for calls in (4). Statements with positive keywords, such as "improvement" (*topic 32*), reduce IV by 0.038 *pp.* and 0.0036 *pp.* for puts and calls in (1) and (4), respectively. The addition of analyst and executive tones in (2) and (5) has no significant effect on the number, magnitude, or significance level of the topic variables. Both options have a negative tone effect, but the analyst tone has a larger magnitude and significance level. It's worth noting that, as predicted by the Put-Call Parity, the majority of the topics have a similar significance and magnitude for both type of options. However, some topics are specific to one type of option, such as *topic 17* for calls, while others, such as *topics 29* and *42* for puts, are discarded during the LASSO stage.

Although the inclusion of fixed (industry) and time (year) effects reduces the number of significant topics in (3) and (6) in Table 6, the main topics for puts (*topic 6, 12, 25, 32 and 35*) and calls (*topic 6, 12, 13, 18 25, 29, 32, 35, and 42*) show little change in terms of coefficient magnitude and significance level. Executive tones are not robust to the addition of time and fixed effects, whereas analyst tone is only relevant for call options.

The contribution of topics to the explanatory power of the features is shown in (2) and (5) in Table 6 , where there is a 44% increase in adjusted R^2 for puts and 38% for calls when including these variables to the baseline specifications in (1) and (5) in Table 5. After controlling for time and fixed effects in (3) and (6) in Table 6, the contribution of topics increases to around 48% for puts and remains constant for calls, relative to the baseline specifications in (4) and (8) in Table 5.

5.2. Implied volatility and executive answers

This set of results explores the impact of executive responses on the change in IV. The methodology is similar to the previous analysis, but now includes topics generated from the highest ranked parametrization for executive statements ($\underline{K} = 43$, $\eta = max()$, and $\rho = 0.5$). The selected coefficients of Equation 6 after the LASSO stage are presented in Table 7. For a comprehensive list of topics and their effect on all targets, refer to Table B.3 in the appendix.

Topics from executive answers in Table 7, like analyst topics, are interpretable and have the expected sign. Answers implying large-scale transactions (*topic 8*) or premiums in trade contracts (*topic 33*) increase uncertainty perception, whereas answers containing positive words, such as "opportunity" in *topic 15* or "strong performance" in *Topic 35*, decrease it. The addition of tone variables in (2) and (5) has no effect on topic coefficients or their significance level. As with analyst

Table 7: Puts and calls with 30 days maturity, Topics from executive answers and tones

	$ln\Delta Put^{30}$			$ln\Delta Call^{30}$		
	(1)	(2)	(3)	(4)	(5)	(6)
const	-0.16	-0.168	-0.245	-0.135	-0.144	-0.236
	(0.093)*	(0.093)*	(0.101)**	0.098	0.098	(0.1)**
topic 5	-0.049	-0.049	-0.048	-0.056	-0.056	-0.056
brand target goal	(0.018)***	(0.018)***	(0.015)***	(0.014)***	(0.014)***	(0.01)***
topic 7	-0.02	-0.02	-0.026	-0.019	-0.019	-0.024
product client launch	(0.006)***	(0.006)***	(0.007)***	(0.006)***	(0.006)***	(0.006)***
topic 8	0.056	0.055	0.043	0.056	0.054	0.041
large deal transaction	(0.012)***	(0.012)***	(0.011)***	(0.012)***	(0.011)***	(0.013)***
topic 9	0.056	0.054	0.046	0.059	0.057	0.048
cycle correct scenario	(0.012)***	(0.014)***	(0.007)***	(0.01)***	(0.012)***	(0.007)***
topic 11	-0.023	-0.024	-0.016	-0.023	-0.024	-0.017
price pressure volume	(0.007)***	(0.007)***	(0.009)*	(0.006)***	(0.006)***	(0.008)**
topic 15	-0.02	-0.016	-0.007	-0.019	-0.016	-0.006
opportunity store focus	(0.008)**	(0.008)**	(0.004)*	(0.008)**	(0.007)**	(0.004)
topic 24	0.024	0.025	0.025	0.024	0.025	0.025
technology product platform	(0.008)***	(0.008)***	(0.011)**	(0.008)***	(0.008)***	(0.011)**
topic 31	-0.013	-0.013	-0.015	-0.003	-0.012	-0.013
europe china market	(0.007)*	(0.007)*	(0.005)***	(0.008)	(0.008)	(0.005)**
topic 33	0.041	0.04	0.034	0.037	0.036	0.029
contract trade premium	(0.011)***	(0.011)***	(0.011)***	(0.012)***	(0.012)***	(0.013)**
topic 35	-0.016	-0.014	-0.007	-0.015	-0.013	-0.005
expect strong performance	(0.004)***	(0.004)***	(0.004)**	(0.003)***	(0.003)***	(0.002)**
$AnaTone$		-0.924	-0.462		-1.174	-0.694
		(0.423)**	0.423		(0.353)***	(0.352)**
$ExeTone$		-0.526	-0.366		-0.553	-0.402
		0.367	0.336		(0.3)*	0.274
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs	13759	13759	13759	13759	13759	13759
Adj. R^2	0.066	0.069	0.061	0.064	0.068	0.06
Effects	none	none	time+ind	none	none	time+ind

Note: $ln\Delta Put^{30}$ and $ln\Delta Call^{30}$ denotes the log of the contemporaneous change in ATM IV for puts and calls with 30 days maturities respectively. Clustered standard errors. *, **, and *** indicate significance at the 10%, 5% and 1% critical level, respectively.

statements, the majority of the topics in executive statements are robust to time and industry effects in (3) and (6). In fact, only *topic 15* out of the top-ten topics for calls becomes statistically not different from zero after these effects are taken into account.

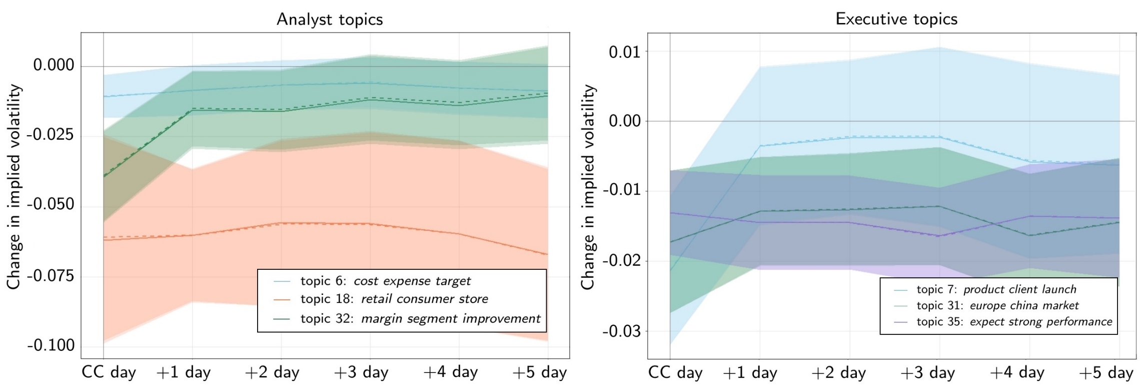
In terms of explanatory power, topics from executive replies represent a substantial information gain over the baseline specification in Tables 5 columns (1) and (2). The difference in adjusted R^2 between (2) and (5) in Table 7 is in the order of 176% and 140%, respectively, and 182% and 136% when time and fixed effects are controlled for. The gain in exploratory power when using topics from executive statements instead of topics from analyst statements accounts for 90% and 71% for puts and calls, respectively (see (3) and (6) in Tables 6 and 7).

In summary, the topics generated from the Q&A portion of earnings conference calls between executives and analysts provide additional information that helps to explain the contemporaneous change in IV. Our approach results in interpretable topics with the expected sign in most cases and topics that are similar in magnitude between calls and puts, which conform to the Put-Call Parity principle. Furthermore, the majority of topics have negative coefficients, in line with previous research (Donders et al., 2000; Isakov and Perignon, 2001) that suggests that IV for both types of options decreases after information from the conference calls is disclosed. The dynamics of this decrease is influenced by leverage effects, which depend on good or bad news disclosed during the session. Finally, the tone variables behave similarly when combined with analyst or executive topics. As in Borochin et al. (2018), manager tones are not statistically significant, and only analyst tones are statistically significant when combined with topic information; however, in our case, analyst tones are not robust to time and fixed effects when $ln\Delta Put^{30}$ is used as a dependent variable.

5.3. Post-event dynamics and component contribution

This section presents the dynamic responses of participant statements up to 5 days following the earnings event, as well as component contribution by feature type (topics, tones, or controls). For the dynamic responses, we recover the $\{\hat{\beta}_k\}_{h=1}^{H=5}$ coefficients in Equation 6 for $h = 0, 1, \ldots, 5$ in the dependent variable. Figure 3 depicts the dynamic responses of changes in IV of puts and calls with a maturity of 30 days to selected analyst and executive topics.

Figure 3: Impulse responses to selected topics

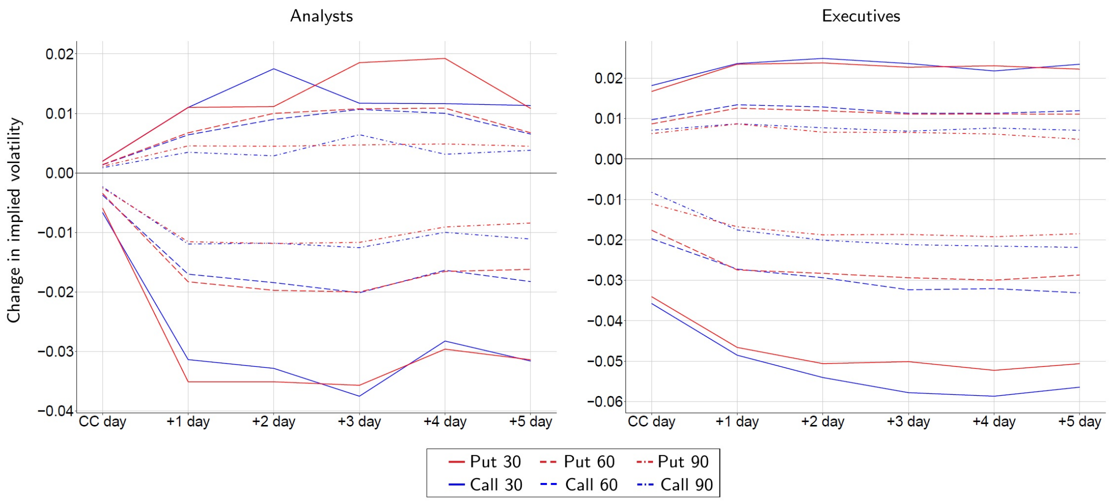


Note: This figure plots the estimated coefficients β_h in Equation 6 against h. Solid lines denote the effect on the IV of puts while dashed lines denote the effect on calls. Shaded areas represent confidence bands at the 5^{th} to 95^{th} percentile range based on robust standard errors.

We can distinguish two types of topic responses from both panels in this figure: short-lived and long-lived responses. The first type, such as *topic 32* for analyst questions and *topic 7* for executive responses, is significant on the day of the event but becomes statistically insignificant afterwards. The second type of response is more persistent and remains significant throughout the estimation window, as seen in *topics 18* and *35* for analyst questions and executive answers, respectively.

We now move on from the individual topic perspective to investigate the aggregated dynamics of topics and tones. Figure 4 presents the average change in IV of puts and calls with different maturities for topics from analyst questions and executive answers grouped by effect sign. The mean responses to positive and negative topics in period $h = 0, \ldots, 5$ are calculated by adding the marginal effect at the mean (MEM) value for coefficients with the same sign and a p-value strictly less than 0.1.

Figure 4: Post-event effect topics, mean values

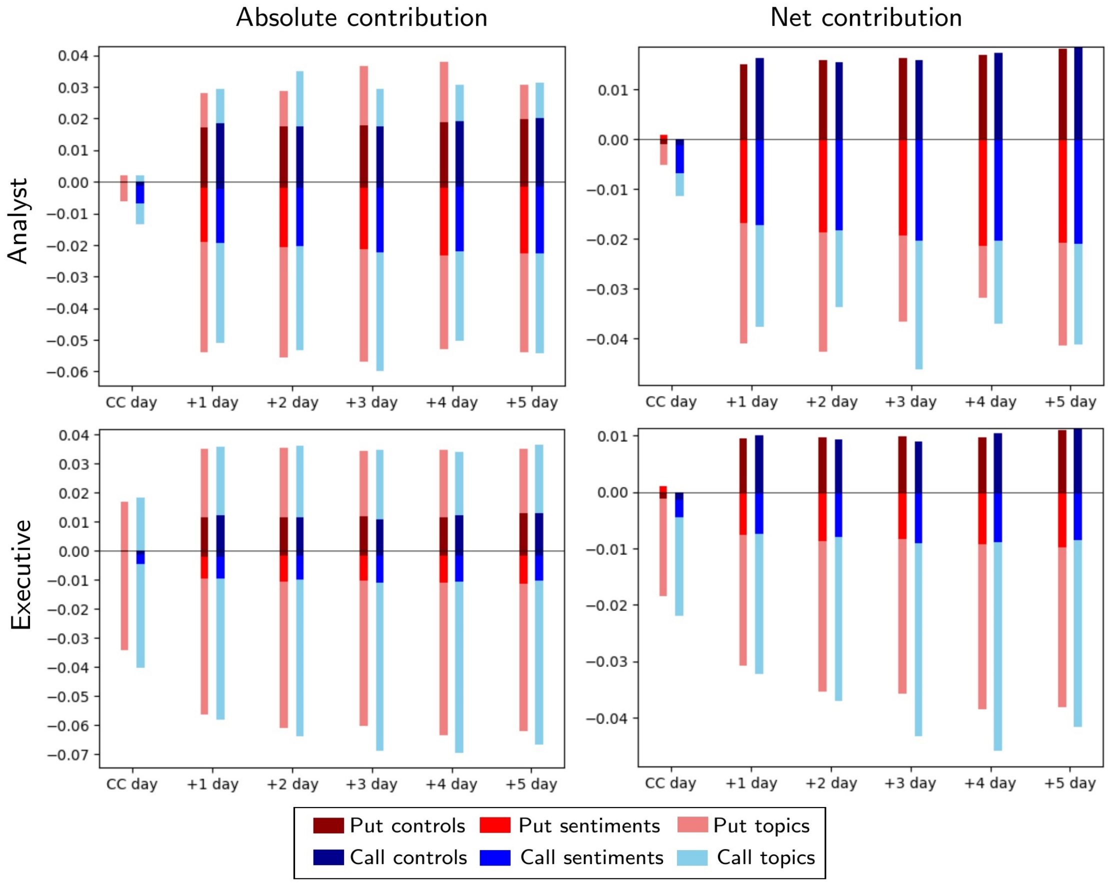


Note: This figure plots the estimated Marginal Effect at the Mean (MEM) grouped by sign against h.

The left panel of Figure 4 shows that the contemporaneous response, h = 0, of targets with 30, 60 and 90 day maturities to both positive and negative topics is small and increases substantially one day after the event before remaining at a low varying level for the rest of the estimation window. The patterns in the left panel contrast with those on the right panel for executive responses, where the contemporaneous response is larger and the subsequent response is less pronounced, as in the analyst case, with no clear indication of mean reversion in the short period. Overall, negative responses outweigh positive responses in terms of magnitude, implying a negative net effect (decreasing uncertainty) of participants' statements. In both cases, the effect of topics is greater when considering short-term maturities, and it decreases with increasing expiration horizon, coinciding with the decreasing functional form of IV (Canina and Figlewski, 1993).

The following figure takes a deeper look into the individual contributions of tones, topics, and controls to change in uncertainty perception. Figure 5 summarizes the absolute and net contribution of each component to the change in IV for puts and calls with a maturity of 30 days, given a set of participant statements. As in the previous figure, values are expressed in terms of MEM, grouped by sign, and exclude coefficients that are not statistically significant from zero at the 10% level.

Figure 5: Contribution to IV change by component, Maturity 30 days



Note: This figure plots the absolute and net contributions of topics extracted from analyst question and executive answers. The contribution is based on the Marginal Effects evaluated at the Mean (MEM).

The top panels of Figure 5 present a summary of the absolute and net impact of analyst statements on the changes in IV. Despite the positive contribution (uncertainty increasing) of controls, the prevalence of topics with negative coefficients led to a net reduction in uncertainty perception. The primary drivers of the contemporaneous decline in IV for put options were topics, with a magnitude of 0.0040 pp. Conversely, (analyst) tone exerted a more significant effect on the contemporaneous change in call options, with a magnitude of 0.0056 pp, followed by topics with a magnitude of 0.0047 pp. In the aftermath of the conference call event, the increasing proportion of components with negative coefficients contributed to the decline in IV. The net effect of both analyst tones and topics was negative, with a similar magnitude. For call options, analyst tones had a more pronounced impact on IV than topics on days 2, 4, and 5. For put options, analyst tones dominated topics in their impact on IV on days 3, 4, and 5.

The lower panels of Figure 5 summarize the contribution of features from executive answers to the change in IV. Unlike analyst statements, the positive controls outweight the negative ones. The contemporaneous effect of executive answers is driven primarily by topics in both puts and calls options, with a small contribution from tones in the latter. In comparison to analyst statements, the difference in the magnitude of the contemporaneous effect and the effect in the following days is less pronounced. In the aftermath of the conference call event, the role of analyst tones in the decline of IV increases, however topics remain the main driving force behind the reduction in IV.

6. Effect of analyst and executive statements on the volatility spread

The final set of results focuses on the IV spreads, i.e., deviations from put-call parity in terms of IV. The use of volatility spreads as a predictor of future returns is well-established in the literature (Cremers and Weinbaum, 2010). A negative difference in IV between call and put options results in a negative spread, which could signify future negative returns, as demonstrated by Du et al. (2018). Table 8 presents the results of the fixed-effect model in Equation 6, where the dependent variable are volatility spreads, computed as in Equation 2, and the independent variables are topics generated from analyst questions. Columns 1, 3, and 5 in this table show the regression results for spreads with 30, 60, and 90 days maturities based solely on topics from analyst questions. Columns 2, 4, and 6 extend the model by adding analyst and executive tones. Topic variables were discarded during the LASSO step in all specifications in this table, therefore only tones and controls entering in the inference stage as independent variables.

The constant term is significant in all regressions of Table 8 and increases with the expiration horizon, indicating a systematic deviation from Put-Call parity driven by the IV of puts. As in previous results, executive tones are not significant while analyst tones are positive and significant. The positive coefficient may suggest an increase in the IV for calls compared to puts. This is generally considered a signal of a positive outlook for the underlying stock, as investors are willing to pay a higher premium for the call options in anticipation of future positive returns.

Now we turn to the effect of executive statements on volatility spreads. Our

Table 8: Spreads with 30, 60 and 90 days maturity, topics from analyst questions

	$spread^{30}$		$spread^{60}$		$spread^{90}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Const	-0.063	-0.060	-0.080	-0.077	-0.094	-0.090
	(0.024)***	(0.024)**	(0.020)***	(0.020)***	(0.023)***	(0.028)***
$AnaTone$		0.314		0.291		0.383
		(0.106)**		(0.055)***		(0.065)***
$ExeTone$		0.102		0.084		0.046
		(0.153)		(0.094)		(0.079)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs	13759	13759	13759	13759	13759	13759
$Adj.R^2$	0.003	0.004	0.005	0.006	0.006	0.007
Effects	ind	ind	ind	ind	ind	ind

Note: Clustered standard errors. $spread^M$ denotes ATM IV spread with $M = 30, 60$, and 90 days maturities. *, **, and *** indicate significance at the 10%, 5% and 1% critical level, respectively. Industry effects specification for all regressions.

Table 9: Spreads with 30, 60 and 90 days maturity, topics from executive answers

	$spread^{30}$		$spread^{60}$		$spread^{90}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Const	-0.054	-0.052	-0.072	0.063	-0.088	-0.086
	(0.024)**	(0.024)**	(0.021)**	(0.027)**	(0.024)***	(0.023)***
Topic 15	0.005	0.005	0.003	0.003	0.004	0.004
opportunity store focus	(0.001)***	(0.002)***	(0.001)**	(0.001)**	(0.001)**	(0.001)***
Topic 35	0.004	0.003	0.003	0.002		
expect strong performance	(0.001)**	(0.002)**	(0.001)**	(0.001)**		
$AnaTone$		0.345		0.279		0.356
		(0.127)***		(0.056)***		(0.061)***
$ExeTone$		-0.062		-0.033		-0.055
		(0.172)		(0.112)		(0.079)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs	13759	13759	13759	13759	13759	13759
$Adj.R^2$	0.004	0.004	0.005	0.006	0.006	0.007
Effects	ind	ind	ind	ind	ind	ind

Note: Clustered standard errors. $spread^M$ denotes ATM IV spread with $M = 30, 60$, and 90 days maturities. *, **, and *** indicate significance at the 10%, 5% and 1% critical level, respectively. Industry effects specification for all regressions.

results, summarized in Table 9, show a similar pattern for intercept and tone coefficients relative to those from analyst results. However, in the case of executive results, after applying LASSO selection, two distinct topics emerge as significant: *topic 15* (*opportunity store focus*) and *topic 35* (*expect strong performance*). Both topics are also significant in Table 9 and exhibit a negative coefficient there. This reduction in IV is reflected in positive coefficients in able 9, suggesting a positive outlook for the underlying stock and thus, potential positive returns. Additionally, our results show a marginal increase in the adjusted R^2 with the expiration horizon and that the contribution of topics in terms of R^2 remains minimal compared to a specification relying solely on participant tones.

This relationship between the volatility spread, the IV of calls and puts, and positive stock returns highlights the importance of monitoring market sentiment when analyzing financial markets.

7. Robustness

We conduct several robustness checks[9] on our main specifications for both analyst and executive statements, which indicate that the significance of topics remains robust to the inclusion of tones, fixed and time effects, and varies only in terms of composition of significant topics. The adjusted R-squared increases with maturity, indicating that information from executives and analysts is more relevant for options with longer expiration horizons (see Appendix C). We test different time and fixed effects specifications, including 6-digit industry effects (Appendix D), quarter-time effects, and quarter-year time effects, and find that topics remain significant and typically outweigh tones regardless of maturity level. Our results indicate that the inclusion of tones or controls in the LASSO stage leads to a reduction in non-significant topics and controls in the second stage, but does not alter the distribution, magnitude, or significance level of the main topics and tones. We also test for sub-optimal specifications and find that the relationship between topics and tones remains consistent with our main results at all maturity levels, despite slight changes in distribution and coefficient magnitudes.

8. Conclusion

This study presents a unique approach to measuring the impact of information shared during earnings conference calls on investors' uncertainty perception of a firm's value. By analyzing a vast dataset of 494,600 analyst questions and 431,862 executive answers, we used a statistical topic model strategy to extract topics and tones from the content. Our analysis enables us to differentiate between the contribution of topics and tones to changes in implied volatility (IV) of ATM calls and puts with up to 90 days maturities.

[9] Due to space limitations, some robustness checks are not included. They can be provided upon request.

Using LDA, we retrieved the main narratives, represented by topics, at the statement level for each type of participant. We found that incorporating topics from both analyst questions and executive replies improved the model's explanatory power for changes in IV. We also discovered that executive statement topics contribute to larger information gains, while tones from analyst statements are the outweighs the net contribution of analyst topics. Moreover, we examined the influence of topics on option IV spreads and found that topics from executive statements and tones from analyst questions can explain a small fraction in the deviations from put-call parity.

Overall, our findings underscore the importance of analyzing both topics and tones to better understand the impact of information conveyed during earnings conference calls. This information can be used to construct trading strategies that take advantage of investor sentiment and expectations for future earnings.

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Appendices

A. Topic model estimation and selection

A.1. Data structure and pre-processing

We define the data structure for our analysis as follows:

$$Call_{i,t} = \sum_{q=1}^{Q} Question_{q,i,t} + \sum_{a=1}^{A} Answer_{a,i,t}$$

Here, i represents a company listed on the $S\&P500$ during the sample period, and t indicates the date of the conference. The questions and answers are separated, creating individual documents for each. The LDA topic model generates a common set of K topics for all documents (questions or answers) within a conference call, and across all calls in the sample. In addition, the topic weight[10] for each document is computed, defining the document as the sum of individual topic weights and an error term θ in cases where the topic model does not fit any of the K estimated topics.

$$Document_{d,i,t} = \sum_{k=1}^{K} Prob_{k,d,i,t} + \theta$$

A.2. Topic modeling with LDA

The generative model for the LDA, as described in Blei et al. (2003), consists of the following steps.

1. Determine term distribution, β, for each topic, which is given by:

$$\beta \sim Dirichlet(\delta)$$

2. Determine proportions, θ , of the topic distribution for each document, w:

$$\theta \sim Dirichlet(\alpha)$$

3. For each of the N words w_i:
   (a) Choose a topic $z_i \sim Multinomial(\theta)$.
   (b) Choose a word w_i from a multinomial probability distribution conditioned on the topic $z_i : p(w_i|z_i, \beta)$.

[10] We prefer to use the word 'weights' instead of 'probabilities' since their sum is not coerce topics to add to one.

This model is estimated using the Gibbs sampling, as proposed in Griffiths and Steyvers (2004). Draws from the posterior distribution $p(z|w)$ are obtained by sampling from:

$$p(z_i = K|w, z_i) \propto \frac{n^{(j)}_{-i,K} + \delta}{n^{(.)}_{-i,K} + V\delta} \frac{n^{(d_i)}_{-i,K} + \alpha}{n^{(d_i)}_{-i} + k\alpha} \tag{A.1}$$

The dot (.) implies that summation over the index is performed. The hyperparameter α, prior parameter for the distribution of topics over documents, is set to $1/K$, and δ, prior parameter for the distribution of words over topics, is set to 0.1. The optimal number of topics $K = K^*$ will be defined in the next section.

Estimates $\hat{\beta}$ and $\hat{\theta}$ are given by:

$$\hat{\beta}^{(j)}_K = \frac{n^{(j)}_K + \delta}{n^{(.)}_K + V\delta} \qquad \hat{\theta}^{(d)}_K = \frac{n^{(d)}_K + \alpha}{n^{(d)} + k\alpha} \tag{A.2}$$

The log-likelihood is given by:

$$log(p(w)) = \sum_{d=1}^{D} \sum_{j=1}^{V} n^{(jd)} log \left[\sum_{K=1}^{k} \theta^{(d)}_k \beta^{(d)}_k \right] \tag{A.3}$$

For simplicity we assume for symmetric (uniform) priors for θ and β. We approximate the prior number of topics for each sample as the range around the number of topics where median coherence maximal is for the complete sample.

We allocate 80% of the documents to the training sample and the remaining 20% to the test sample. Table 3 summarizes the distribution of documents over samples.

A.3. Topic model evaluation

We evaluate topics models based on three criteria: Topic intrusion, coherence and perplexity. Topic intrusion measures the human interpretability of the generated topic label (Here defined as three of the first five words in a topic), and the number of interpretable topics out of the total number of topics. Interpretability of a topic is summarized in given by the word intrusion (wi_k) score:

$$wi_k = \sum_{w=1}^{5} \text{word score}_w \tag{A.4}$$

Where word score_w is 0 for an intrusive word (i.e. "John", "hello", "big"), 0.1 for a neutral word (i.e. "strong", "performance", "expect"), and 0.2 for a meaningful word (i.e. "investment", "demand", "risk"). If $wi_k \leq 0.5$ then the topic is discarded.

$$intrusion(K) = \frac{\text{\# of discarded topics}}{K} \tag{A.5}$$

The second criterium is topic coherence, which provides a rank for topic models by measuring the degree of semantic similarity between high-scoring words within a set of topics. These measurements help to identify topics that are semantically interpretable topics and topics that are artifacts of statistical inference Stevens et al. (2012). The coherence measure proposed is based on co-occurrences of word pairs within the corpus used to train the topic model. Given an ordered list of words $T_k = w_1, \ldots, w_n$, for each resulting topic $k \in K^*$, the UMass-coherence is defined as:

$$coherence(K) = \sum_{m=2}^{M} \sum_{m-1}^{l} log \frac{p(w_m, w_l) + \frac{1}{D}}{p(w_l)} \tag{A.6}$$

The smoothing count $1/D$ is added to avoid calculating the logarithm of zero. These measures are calculated for a series of models with different values for K.

The final criteria is the perplexity, which is obtained based on the forecast error when fitting an unseen chunk of documents as evaluation corpus. We can define perplexity as the inverse probability of the test set, normalised by the number of words.

$$perplexity(K) = 2^{-\frac{1}{N} log_2 P(w_1, w_2, \ldots, w_N)} \tag{A.7}$$

The best topic model is the one that minimizes at the same time in in-sample error (Topic intursion and $-1\times$topic coherence) and out-sample error (perplexity). We rank models as follows:

$$\begin{aligned} rank^{text}(K) =& 0.25 \times rank(min\{-coherence(K)\})+ \\ & 0.25 \times rank(min\{intrusion(K)\})+ \\ & 0.50 \times rank(min\{perplexity(K)\}) \end{aligned}$$

The best ranked models for LDA and BERT will be selected as our working topic models. Table A.1 provides an example of a topic model selection matrix for executive's answers, using LDA topic generating algorithm.

A.4. Feature model evaluation

We evaluate feature models based on loss functions for the train and test samples, and the AIC criterion. Loss functions are defined as follows:

Table A.1: Topic model evaluation for section executive's answers, LDA topic generating algorithm)

topics	# $intrusion$	$rank^{coherence}$	$rank^{intrusion}$	$rank^{perplexity}$	$rank^{text}$
42	9	3	3	2	**1**
45	9	6	2	3	2
43	10	9	**1**	4	3
44	10	10	4.5	**1**	4
37	12	2	10	6	5
40	9	8	4.5	8	6
41	14	4	11	5	7
36	9	**1**	8	10	8
35	9	5	6.5	11	9
39	12	7	9	7	10
38	10	11	6.5	9	11

$$loss\ function = mse_{sample} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \check{y}_i)^2 \tag{A.8}$$

The AIC criterion is given by:

$$aic = 2K - 2ln(\hat{L}(\beta, \gamma, \psi \mid \hat{x}_{s,q}^{p,k}, c_{s,q}, sent_{s,q})) \tag{A.9}$$

where $\hat{L}$ is the maximum value for the likelihood for the evaluated model.

We define the best feature model for a given target as the one that provides best in-sample and out-of-sample performance, in terms of minimizing the loss functions in Equation A.8. We account also for sparsity given an small rank weight to models with small AIC. We rank models as follows:

$$\begin{aligned} rank_{feature}^{M=\{30,60,90\}}(K) =& 0.4 \times rank(min\{mse_{train}(K)\})+ \\ & 0.4 \times rank(min\{mse_{test}(K)\})+ \\ & 0.2 \times rank(min\{aic(K)\}) \end{aligned}$$

Since we look for the best set of features that explain, at the same time, all type of targets at all maturity levels, we summarize model rankings first by targets and then by maturities. In the aggregate ranking by type of targets all targets with the same maturity, calls, puts and spreads, are weighted equally. In the final step we compute the final feature ranking over all maturities as follows:

$$
\begin{aligned}
rank^{feature}(K) =& 0.5 \times rank^{M=30}_{feature}(K) + \\
& 0.3 \times rank^{M=60}_{feature}(K) + \\
& 0.2 \times rank^{M=90}_{feature}(K)
\end{aligned}
$$

We give higher weights to short term maturities since the change in IV is a decreasing function of the time-to-option expiration horizon Canina and Figlewski (1993). Table A.2 provides an example of a feature model selection matrix for executive's answers, using LDA topic generating algorithm.

Where $\tilde{x}^P_{j,s,q}$ is combination of topics, $\hat{x}^P_{k,s,q}$ and controls, $c_{c,s,q}$, with $J = K + C$. We keep the tone variables, $\psi_i sent_{i,s,q}$, in every possible specification.

Table A.2: Feature model evaluation for section executive's answers, LDA topic generating algorithm, 30 days Maturity

			ranking Δput^{30}			ranking $\Delta call^{30}$			ranking $spread^{30}$			
topics	agg. fct.	thres.	mse_{train}	mse_{test}	aic	mse_{train}	mse_{test}	aic	mse_{train}	mse_{test}	aic	**Rank M=30**
44	max	0.5	1	3	10	1	2	10	3	3	10	1
43	max	0.5	3	7	5	2	8	4	11	4	4	2
39	max	0.5	4	2	9	3	3	9	2	10	8	3
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
40	mean	0.5	6	8	4	4	7	5	8	5	5	5
41	mean	0.5	5	1	11	8	1	11	6	1	11	6
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
38	max	0.75	7	4	8	7	5	8	9	2	7	7
45	max	0.75	8	11	1	5	11	1	4	8	9	8
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
35	mean	False	9	5	7	9	4	7	5	11	1	9
37	mean	False	10	6	6	11	6	6	1	9	6	10
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

The best model overall for each participant and each feature generation algorithm is given by:

$$rank(K)^{overall} = 0.5 \times rank^{topic}(K) + 0.5 \times rank^{feature}(K)$$

Such that the best model is the best model in terms of interpretability and explanatory performance. Table A.3 provides an example of the overall model selection matrix for executive's answers, using LDA topic generating algorithm.

Table A.3: Final model evaluation for section executive's Answers, LDA topic generating algorithm

Topics	Agg fct	Threshold	Rank $M = 30$	Rank $M = 60$	Rank $M = 90$	Rank topic model	**Final Rank**
43	max	0.5	2	2	1	3	1
44	mean	0.5	1	1	5	4	2
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
45	mean	0.5	8	9	11	2	5
41	max	0.75	6	3	3	7	6
37	mean	False	10	10	4	5	7
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

B. Further Results

Table B.1: Variable description

Variable	Description
$ln\Delta Put$	Log change in ATM IV of an put with maturity $M = (30, 60, 90)$.
$ln\Delta Call$	Log change in ATM IV of an call with maturity $M = (30, 60, 90)$.
$spread$	Log IV spreads, it is given by the difference between the IV of a call and a put option for the same underlying asset s, with the same maturity M.
$Return$	Daily return at the conference (dividend adjusted).
$Momentum$	5 trading day pre-event stock return.
$BmRatio$	Book-to-market ratio: Most recent book value per share divided by price
$EpsSurp$	Earnings surprise: Mean earnings-per-share forecast less matched actual value from the earnings event covering quarter q, divided by price.
$Mvlog$	Market value: Common logarithm of the firm's market capitalization at the day of the earnings event.
$AnaTone$	Sentiment of analyst statements for a Q&A session.
$ExeTone$	Sentiment of executive statements for a Q&A session.
$AnaQues$	Number questions in the Q&A session.
$ExeAns$	Number answers in the Q&A session.
$Topic$	Topic weights from the LDA models for either analyst questions. or executive answers

B.1. *LDA topics and sign effect*

Table B.2: Topics for analyst questions with sign effect

Topic	Keywords	30 days maturity		60 days maturity		90 days maturity	
		$ln\Delta Put$	$ln\Delta Call$	$ln\Delta Put$	$ln\Delta Call$	$ln\Delta Put$	$ln\Delta Call$
0	production, run, rig	ne	ne	ne	ne	ne	le
2	growth, guidance, revenue	ne	ne	ne	ne	le	ne
4	data, patient, response	ne	ne	ne	ne	ne	ne
5	system, network, distribution	le	le	le	(+)	le	le
6	cost, expense, target	$(-)^*$	$(-)^*$	$(-)^*$	$(-)$	$(-)^*$	$(-)$
8	backlog, brazil, hedge	le	le	le	le	le	le
9	plan, update, timing	le	le	$(+)^*$	$(+)^*$	$(+)^*$	ne
10	seeing, trend, demand	ne	ne	ne	ne	le	ne
11	capex, project, spending	ne	ne	ne	ne	ne	ne
12	market, supply, global	$(+)^*$	$(+)^*$	$(+)^*$	$(+)^*$	$(+)^*$	$(+)^*$
13	unit, confidence, visibility	(+)	$(+)^*$	ne	(+)	le	(+)
14	opportunity, potential, deal	le	ne	ne	ne	le	ne
16	share, program, gain	le	le	le	ne	le	le
17	capital, risk, loss	ne	$(+)^*$	$(+)^*$	$(+)^*$	$(+)^*$	$(+)^*$
18	consumer, store, retail	$(-)$	$(-)^*$	$(-)$	$(-)^*$	$(-)$	$(-)^*$
19	benefit, tax, cash flow	le	le	le	le	le	le
20	fund, online, legacy	le	le	le	le	le	le
22	product, line, development	le	le	le	le	le	ne
23	portfolio, loan, balance	le	le	le	le	le	le
24	sale, asset, percentage,	le	le	le	le	le	le
25	customer, order, platform	$(+)^*$	$(+)^*$	$(+)^*$	$(+)^*$	$(+)^*$	$(+)^*$
26	building, enterprise, event	(+)	(+)	ne	(+)	le	le
27	issue, specific, challenge	le	le	le	le	le	le
28	year, half, expect	ne	$(-)$	ne	$(-)$	le	ne
29	level, inventory, industry	le	$(-)^*$	le	$(-)^*$	le	$(-)^*$
30	contract, premium, structure	le	le	le	le	le	le
31	service, core, cycle	le	ne	le	le	le	le
32	segment, improvement, performance	$(-)^*$	$(-)^*$	$(-)^*$	$(-)^*$	$(-)^*$	$(-)^*$
35	pricing, volume, gross margin	$(-)^*$	$(-)^*$	$(-)^*$	$(-)^*$	$(-)^*$	$(-)^*$
37	investment, focus, longer term	$(+)^*$	ne	ne	ne	ne	ne
39	channel, launch, marketing	le	le	le	le	le	le
40	china, net, exposure	le	le	le	le	le	le
42	rate, capacity, increase	le	$(+)^*$	le	$(+)^*$	le	le

Note 1: (+/-) Sign of statistically significant topic coefficients, at at least at 10% level. LASSO exclusions denoted with "le". Industry and time-effects robust topics denoted with *. Not statistically significant different from 0 denoted as "ne". Regressions include tone variables and the full set of controls.

Note 2: Topics discarded via word intrusion: 1 (ago, today, break), 3 (maybe, little, bit), 7 (q, fiscal, june), 15 (ha, lot, view), 21 (year, look, like), 33 (number, gave, bit), 34 (kind, mean, guess), 36 (yeah, sorry, answer), 38 (million, right, total), 41 (quarter, second, couple).

Table B.3: Topics from executive answers with sign effect

Topic	Keywords	30 days maturity		60 days maturity		90 days maturity	
		$ln\Delta Put$	$ln\Delta Call$	$ln\Delta Put$	$ln\Delta Call$	$ln\Delta Put$	$ln\Delta Call$
5	brand, target, goal	$(-)^*$	$(-)^*$	$(-)^*$	$(-)^*$	$(-)^*$	$(-)^*$
6	project , capacity , production	ne	ne	ne	ne	ne	le
7	product, client, launch	$(-)^*$	$(-)^*$	$(-)^*$	$(-)^*$	$(-)^*$	$(-)^*$
8	large, deal, transaction	$(+)^*$	$(+)^*$	$(+)^*$	$(+)^*$	$(+)^*$	$(+)^*$
9	cycle, correct, scenario	$(+)^*$	$(+)^*$	$(+)^*$	$(+)^*$	$(+)^*$	le
10	material, agreement, ship	$(-)^*$	$(-)^*$	$(-)$	le	le	le
11	price, pressure, volume	$(-)*$	$(-)^*$	$(-)^*$	$(-)^*$	$(-)^*$	$(-)^*$
12	margin, basis point, gross margin	ne	ne	ne	ne	ne	ne
13	process, issue, decision	ne	ne	ne	ne	ne	$(+)^*$
14	data, patient, study	ne	ne	ne	ne	ne	ne
15	opportunity, store, focus	$(-)^*$	$(-)$	$(-)$	$(-)$	$(-)$	ne
16	spend, dollar, marketing	$(-)^*$	$(-)^*$	ne	ne	le	le
17	expense, benefit, efficiency	$(-)^*$	$(-)$	$(-)^*$	$(-)$	$(-)^*$	ne
18	account, partner, payment	ne	ne	ne	ne	le	le
19	demand, supply, economy	ne	$(-)^*$	ne	ne	ne	ne
20	opportunity, investment, capital	ne	ne	ne	$(-)^*$	ne	$(-)^*$
21	building, space, center	$(+)$	$(+)$	ne	$(+)$	le	ne
22	cash, flow, dividend	ne	$(-)^*$	ne	$(-)^*$	ne	ne
23	customer, service , network	$(+)$	$(+)$	$(+)$	$(+)$	$(+)$	$(+)$
24	technology, product, platform	$(+)^*$	$(+)^*$	$(+)^*$	$(+)^*$	$(+)^*$	$(+)^*$
25	work, program, system	$(-)^*$	$(-)^*$	$(-)$	$(-)^*$	$(-)$	$(-)$
27	area, development, stage	ne	$(+)^*$	ne	ne	ne	ne
28	growth, rate, revenue	ne	ne	ne	ne	ne	ne
29	guidance , impact , change	ne	ne	ne	ne	ne	le
31	europe, china, market	$(-)^*$	$(-)^*$	ne	ne	ne	ne
32	risk, credit, equity	ne	ne	ne	ne	ne	ne
33	contract, trade, premium	$(+)^*$	$(+)^*$	$(+)^*$	$(+)^*$	$(+)^*$	$(+)^*$
34	portfolio, asset, yield	$(-)^*$	ne	$(-)^*$	ne	$(-)^*$	ne
35	expect, strong, performance	$(-)^*$	$(-)^*$	$(-)$	$(-)$	$(-)$	$(-)$
36	market, share, competitor	ne	ne	ne	ne	ne	ne
38	plan, funding, laid	ne	ne	$(+)^*$	ne	$(+)^*$	$(+)^*$
40	sale, unit, sell	ne	ne	ne	ne	ne	le
41	business, segment, commercial	$(-)^*$	ne	ne	le	ne	le

Note: (+/-) Sign of statistically significant topic coefficients, at at least 10%. Lasso exclusions denoted with "le". Time-effect robust topics denoted with *. Industry and time-effects robust topics denoted with **. Not statistically significant different from 0 denoted as "ne".

Note 2: Topics discarded via word intrusion: 0 (want, let, talk), 1 (good, pretty, got), 2 (year, million, end), 3 (little bit, seen, level), 4 (quarter, second, look), 26 (day, month, time), 30 (rig, auto, doug), 37 (number, sorry, chris), 39 (going , right , forward), 42 (thing, going, people)

Table B.4: Descriptive statistics volatility variables

	Mean	Std	Min	Max
ATM IV Put 30	46.4501	43.1564	0.0000	2229.4700
ATM IV Put 60	42.6433	34.6631	0.0000	1229.3800
ATM IV Put 90	41.7415	31.2854	0.0000	1059.2000
ATM IV Call 30	45.5195	39.8600	0.0000	1588.2900
ATM IV Call 60	41.9067	34.1575	0.0000	1401.2900
ATM IV Call 90	41.0536	30.7760	0.0000	1667.3100
IV Spread 30	-0.1383	18.2587	-1006.5800	535.9900
IV Spread 60	-0.1298	16.0336	-1068.1800	741.5300
IV Spread 90	-0.2401	14.3276	-706.4100	1513.0000
Δ IV Put 30	5.6416	22.3799	-1218.7300	716.2900
Δ IV Put 60	2.8585	18.6354	-1141.4200	918.0700
Δ IV Put 90	1.8938	15.8052	-915.8400	716.2900
Δ IV Call 30	5.5906	20.8224	-601.6800	716.2900
Δ IV Call 60	2.9766	16.1651	-656.4000	762.7000
Δ IV Call 90	1.9576	13.5527	-878.8600	716.2900

Note:

Table B.5: Descriptive statistics control variables

	Mean	Std	Min	Max
return	0.0008	0.0453	-0.5000	3.2857
abnormal return	0.0009	0.0441	-0.4938	3.2850
pre-drift return	0.0013	0.0835	-0.8000	2.1379
EP surprise	-0.0294	7.5287	-2059.2748	20.2900
BM ratio	0.5232	9.0686	-1951.2539	594.8212
MV log	9.3802	0.7275	3.3800	12.0231

Note:

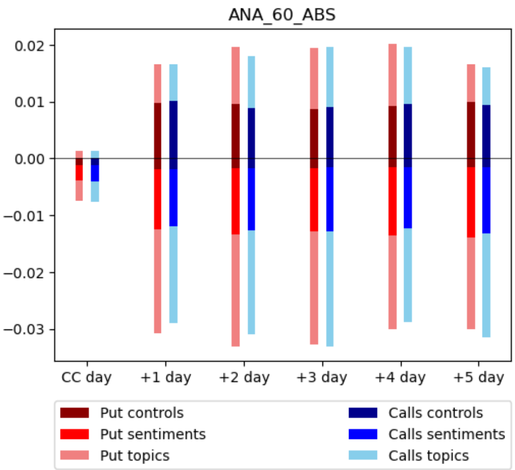
C. Results for 60 and 90 days maturities

Table C.1: Puts and calls with 60 and 90 days maturity, Controls

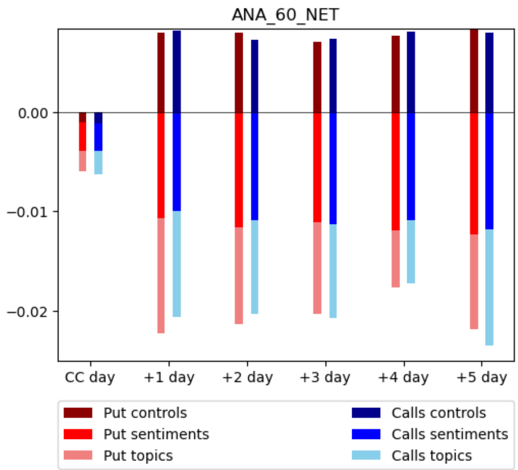
	$ln\Delta Put^{60}$		$ln\Delta Put^{90}$		$ln\Delta Call^{60}$		$ln\Delta Call^{90}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Const	-0.019	-0.029	-0.022	-0.029	-0.013	-0.027	-0.028	-0.04
	(0.071)	(0.069)	(0.052)	(0.05)	(0.071)	(0.071)	(0.05)	(0.05)
Return	-0.013	-0.013	-0.028	-0.028	0.031	0.031	0.029	0.028
	(0.032)	(0.032)	(0.027)	(0.027)	(0.036)	(0.037)	(0.03)	(0.03)
Momentum	-0.287	-0.279	-0.267	-0.261	-0.332	-0.322	-0.315	-0.306
	(0.025)***	(0.024)***	(0.022)***	(0.021)***	(0.026)***	(0.026)***	(0.024)***	(0.024)***
EpsSurp	-0.007	-0.007	-0.024	-0.024	0.005	0.003	0.002	0.001
	(0.023)	(0.022)	(0.022)	(0.022)	(0.007)	(0.006)	(0.005)	(0.005)
BmRatio	0.004	0.003	0.004	0.003	0.005	0.003	0.004	0.003
	(0.004)	(0.004)	(0.003)	(0.003)	(0.005)	(0.005)	(0.004)	(0.004)
Mvlog	-0.004	-0.003	-0.002	-0.001	-0.005	-0.003	-0.001	0
	(0.007)	(0.007)	(0.005)	(0.005)	(0.007)	(0.007)	(0.005)	(0.005)
AnaTone		-0.367		-0.281		-0.422		-0.35
		(0.182)**		(0.147)*		(0.17)**		(0.138)**
ExeTone		-0.239		-0.189		-0.423		-0.37
		(0.173)		(0.13)		(0.181)**		(0.141)***
AnaQues	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ExeAns	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Effects	Ind	Ind	Ind	Ind	Ind	Ind	Ind	Ind
Obs	13839	13839	13847	13847	13840	13840	13847	13847
R^2	0.027	0.03	0.037	0.04	0.032	0.035	0.044	0.048

Note: Clustered standard errors. $ln\Delta Put^M$ and $ln\Delta Call^M$ denotes the log of the contemporaneous change in ATM IV for puts and calls with $M = 60, 90$ days maturities respectively. *, **, and *** indicate significance at the 10%, 5% and 1% critical level, respectively.

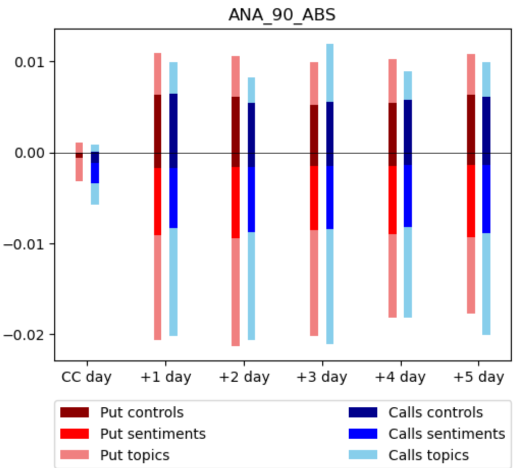
Figure C.1: analysts, contribution to IV change by component, Maturity 60 and 90 days



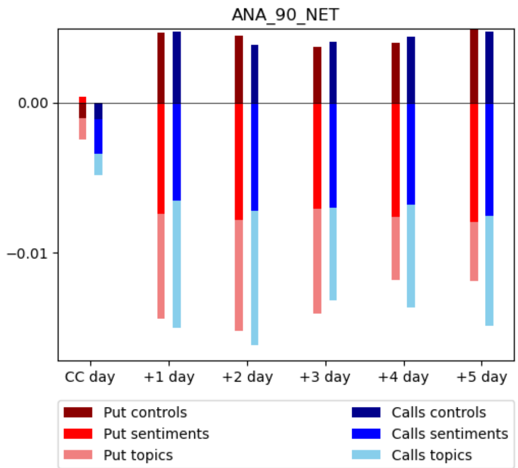
(a) Analyst, absolute contribution, 60 days



(b) Analyst, net contribution, 60 days



(c) Analyst, absolute contribution, 90 days



(d) Analyst, net contribution, 90 days

Note: This figure plots the net contributions of topics extracted from executive answers at 60 and 90 days maturity. The contribution is based on the Marginal Effects evaluated at the Mean (MEM).

Table C.2: Puts and calls with 60 and 90 days maturity, Topics from analyst questions and tones

	$ln\Delta Put^{60}$		$ln\Delta Put^{90}$		$ln\Delta Call^{60}$		$ln\Delta Call^{90}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
topic 4	0.011	0.006	0.011	0.006	0.008	0.004	0.008	0.004
data patient response	(0.006)*	(0.004)	(0.007)	(0.008)	(0.004)*	(0.003)	(0.005)	(0.003)
Topic 6	-0.007	-0.005	-0.007	-0.005	-0.006	-0.004	-0.005	-0.003
cost expense target	(0.003)***	(0.002)*	(0.004)*	(0.003)	(0.002)	(0.002)**	(0.003)*	(0.002)
Topic 9		0.003	0.002	0.003	0.002	0.003	0.002	0.002
plan update timing		(0.001)**	(0.003)	(0.002)*	(0.002)	(0.001)**	(0.001)	(0.001)
Topic 12	0.010	0.013	0.010	0.013	0.008	0.011	0.007	0.008
global market supply	(0.004)**	(0.004)***	(0.002)***	(0.003)***	(0.002)***	(0.003)***	(0.002)***	(0.003)***
topic 13			0.016				0.014	0.012
unit confidence visibility			(0.009)*				(0.008)*	(0.009)
Topic 17	0.005	0.004	0.011	0.012	0.004	0.004	0.008	0.010
capital risk loss	(0.004)	(0.003)*	(0.004)***	(0.003)***	(0.003)	(0.002)**	(0.003)***	(0.002)***
topic 18	-0.032	-0.023	-0.038	-0.029	-0.022	-0.016	-0.023	-0.018
retail consumer store	(0.014)**	(0.015)	(0.013)***	(0.013)**	(0.009)***	(0.010)	(0.008)***	(0.008)**
topic 25	0.017	0.012	0.018	0.013	0.014		0.013	0.009
new platform booking	(0.006)***	(0.003)***	(0.007)***	(0.004)***	(0.005)***		(0.007)*	(0.005)**
Topic 26	0.030	0.013	0.030	0.013				
building enterprise event	(0.017)*	(0.014)	(0.013)**	(0.010)				
topic 32	-0.021	-0.018	-0.022	-0.018	-0.014	-0.012	-0.015	-0.012
margin segment improvement	(0.006)***	(0.006)***	(0.005)***	(0.006)***	(0.003)***	(0.003)***	(0.003)***	(0.004)***
topic 35	-0.021	-0.015	-0.018	-0.011	-0.016	-0.011	-0.012	-0.007
pricing volume gross_margin	(0.004)***	(0.002)***	(0.004)***	(0.002)***	(0.003)***	(0.002)***	(0.003)***	(0.002)***
$AnaTone$		-0.301		-0.329		-0.242		-0.292
		(0.195)		(0.157)**		(0.135)*		(0.027)**
$ExeTone$		-0.224		-0.163		-0.187		-0.183
		(0.222)		(0.180)		(0.200)		(0.158)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	13759	13759	13759	13759	13759	13759	13759	13759
R^2	0.043	0.043	0.047	0.046	0.052	0.053	0.055	0.056
Effects	none	time+Ind	none	time+Ind	none	time+Ind	none	time+Ind

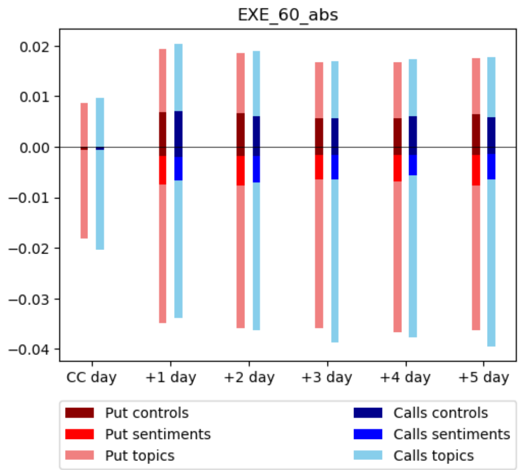
Note: Clustered standard errors. $ln\Delta Put^M$ and $ln\Delta Call^M$ denotes the log of the contemporaneous change in ATM IV for puts and calls with $M = 60, 90$ days maturities respectively. *, **, and *** indicate significance at the 10%, 5% and 1% critical level, respectively.

Table C.3: Puts and calls with 60 and 90 days maturity, Topics from executive answers and tones

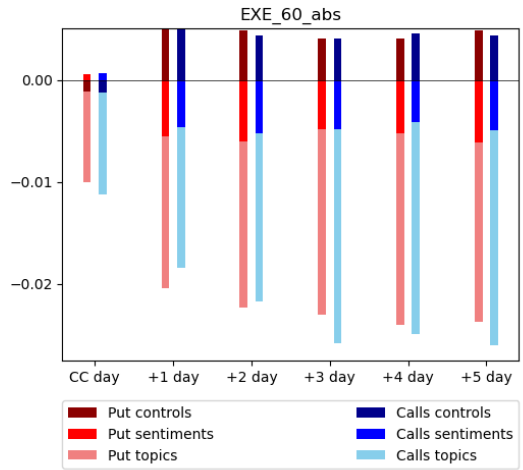
	$ln\Delta Put^{60}$		$ln\Delta Put^{90}$		$ln\Delta Call^{60}$		$ln\Delta Call^{90}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Const	-0.107	-0.16	-0.095	-0.163	-0.079	-0.112	-0.077	-0.118
	(0.054)**	(0.054)***	(0.056)*	(0.053)***	(0.04)**	(0.038)***	(0.039)**	(0.037)***
Topic 5	-0.023	-0.023	-0.03	-0.032	-0.015	-0.016	-0.02	-0.021
brand target goal	(0.011)**	(0.008)***	(0.009)***	(0.006)***	(0.007)**	(0.006)***	(0.007)***	(0.005)***
Topic 7	-0.011	-0.014	-0.012	-0.015	-0.009	-0.011	-0.007	-0.008
product client launch	(0.002)***	(0.003)***	(0.003)***	(0.003)***	(0.002)***	(0.002)***	(0.002)***	(0.002)***
Topic 8	0.033	0.025	0.033	0.026	0.023	0.018	0.022	0.017
large deal transaction	(0.006)***	(0.006)***	(0.007)***	(0.007)***	(0.005)***	(0.004)***	(0.004)***	(0.004)***
Topic 9	0.03	0.023	0.033	0.027	0.022	0.017		
cycle correct scenario	(0.006)***	(0.005)***	(0.007)***	(0.008)***	(0.004)***	(0.003)***		
Topic 11	-0.013	-0.01	-0.012	-0.009	-0.009	-0.007	-0.008	-0.006
price pressure volume	(0.004)***	(0.005)*	(0.003)***	(0.004)**	(0.002)***	(0.003)**	(0.002)***	(0.002)**
Topic 15	-0.01	-0.003	-0.011	-0.003	-0.007	-0.002	-0.006	0.00
opportunity store focus	(0.005)**	(0.003)	(0.005)**	(0.002)	(0.003)**	(0.002)	(0.004)*	(0.002)
Topic 20	-0.003	-0.003	-0.005	-0.004	-0.002	-0.002	-0.004	-0.004
opportunity investment capital	(0.003)	(0.002)	(0.002)**	(0.002)**	(0.002)	(0.002)	(0.002)**	(0.002)**
Topic 24	0.013	0.013	0.014	0.015	0.009	0.01	0.01	0.011
technology product platform	(0.004)***	(0.005)**	(0.004)***	(0.005)***	(0.003)***	(0.004)**	(0.003)***	(0.003)***
Topic 31	-0.006	-0.007	-0.004	-0.005	-0.003	-0.004	-0.003	-0.003
europe china market	(0.004)	(0.003)**	(0.005)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)
Topic 33	0.024	0.021	-0.029	0.025	0.014	0.013	0.018	0.015
contract trade premium	(0.006)***	(0.006)***	(0.008)***	(0.008)***	(0.005)***	(0.006)**	(0.005)***	(0.005)***
Topic 35	-0.008	-0.003	-0.007	-0.002	-0.005	-0.001	-0.005	-0.001
expect strong performance	(0.003)***	(0.003)	(0.002)***	(0.002)	(0.002)**	(0.002)	(0.001)***	(0.001)
Topic 38	0.015	0.014	0.016	0.013	0.014	0.014	0.011	0.009
plan funding laid	(0.009)*	(0.008)*	(0.009)*	(0.009)	(0.006)**	(0.005)***	(0.005)**	(0.005)*
$AnaTone$		-0.332		-0.359		-0.277		-0.31
		(0.216)		(0.15)**		(0.151)*		(0.12)**
$ExeTone$		-0.172		-0.161		-0.179		-0.208
		(0.183)		0.178		(0.169)		(0.159)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	13759	13759	13759	13759	13759	13759	13759	13759
R^2	0.065	0.062	0.067	0.062	0.068	0.065	0.069	0.067
Effects	none	time+ind.	none	time+ind.	none	time+ind.	none	time+ind.

Note: Clustered standard errors. $ln\Delta Put^M$ and $ln\Delta Call^M$ denotes the log of the contemporaneous change in ATM IV for puts and calls with $M = 60, 90$ days maturities respectively. *, **, and *** indicate significance at the 10%, 5% and 1% critical level, respectively.

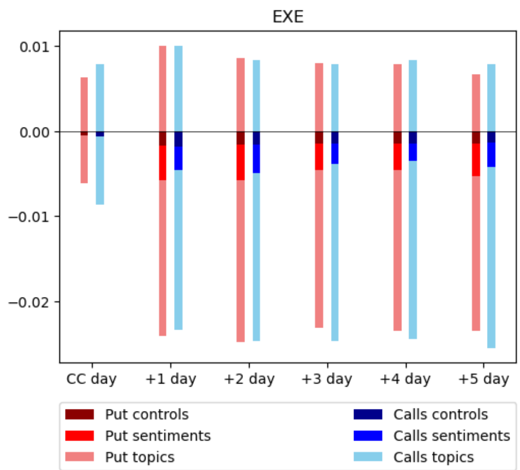
Figure C.2: Executives, contribution to IV change by component, Maturity 60 and 90 days



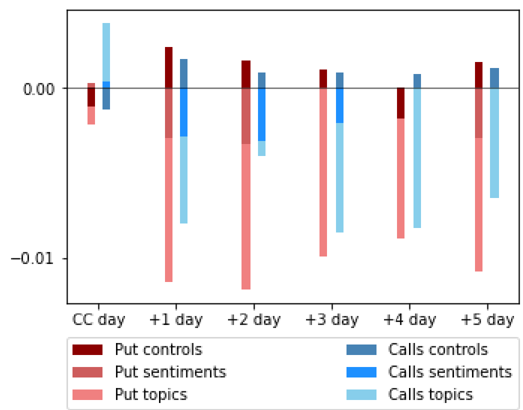
(a) Executive, absolute contribution, 60 days



(b) Executive, net contribution, 60 days



(c) Executive, absolute contribution, 90 days



(d) Executive, net contribution, 90 days

Note: This figure plots the net contributions of topics extracted from executive answers at 60 and 90 days maturity. The contribution is based on the Marginal Effects evaluated at the Mean (MEM).

D. Results for 30 days maturities, 6-digit industry effects

Table D.1: Puts and calls with 30 days maturity, control variables and tones, 6-digit industry effects

	$ln\Delta Put^{30}$				$ln\Delta Call^{30}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Const	-0.137	-0.151	-0.208	-0.052	-0.119	-0.134	-0.197	-0.017
	(0.110)	(0.109)	(0.112)*	(0.12)	(0.109)	(0.109)	(0.112)*	(0.12)
Return	0.120	0.118	0.101	0.034	0.170	0.167	0.151	0.089
	(0.046)***	(0.046)**	(0.046)**	(0.041)	(0.052)***	(0.052)***	(0.053)***	(0.046)*
Momentum	-0.326	-0.302	-0.311	-0.311	-0.385	-0.356	-0.366	-0.367
	(0.036)***	(0.036)***	(0.035)***	(0.03)***	(0.037)***	(0.037)***	(0.037)***	(0.032)***
EpsSurp	0.033	0.03	0.019	-0.010	0.021	0.015	0.011	0.008
	(0.054)	(0.051)	(0.052)	(0.043)	(0.013)	(0.013)	(0.013)	(0.009)
BmRatio	0.016	0.011	0.009	0.003	0.015	0.011	0.008	0.006
	(0.009)*	(0.009)	(0.009)	(0.006)	(0.01)	(0.009)	(0.009)	(0.007)
Mvlog	0.004	0.006	0.012	-0.006	0.002	0.004	0.011	-0.009
	(0.01)	(0.01)	(0.011)	(0.011)	(0.01)	(0.01)	(0.011)	(0.011)
AnaTone		-0.873	-0.467	-0.455		-1.166	-0.731	-0.732
		(0.372)**	(0.353)	(0.274)*		(0.357)***	(0.343)**	(0.266)***
ExeTone		-1.034	-0.901	-0.588		-0.951	-0.787	-0.554
		(0.49)**	(0.501)*	(0.282)**		(0.497)*	(0.502)	(0.272)**
AnaQues	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)*
ExeAns	0.000	0.000	0.000	0.000	-0.001	-0.001	-0.001	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)*	(0.000)**	(0.000)*	0.000
Obs	13805	13805	13805	13805	13805	13805	13805	13805
Adj. R^2	0.019	0.023	0.022	0.017	0.023	0.028	0.026	0.023
Effects	none	none	year	Ind	none	none	year	Ind

Note: Clustered standard errors. $ln\Delta Put^{30}$ and $ln\Delta Call^{30}$ denotes the log of the contemporaneous change in ATM IV for puts and calls with 30 days maturities respectively. *, **, and *** indicate significance at the 10%, 5% and 1% critical level, respectively.

Table D.2: Puts and calls with 30 days maturity, selected topics from analyst questions and tones, 6-digit industry effects

	$ln\Delta Put^{30}$				$ln\Delta Call^{30}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Const	-0.135	-0.150	-0.204	-0.047	-0.123	-0.139	-0.198	-0.023
	(0.107)	(0.107)	(0.11)*	(0.119)	(0.104)	(0.104)	(0.108)*	(0.117)
Topic 6	-0.012	-0.011	-0.011	-0.006	-0.012	-0.011	-0.011	-0.005
cost expense target	(0.005)**	(0.005)**	(0.005)**	(0.004)	(0.004)***	(0.004)**	(0.004)**	(0.004)
Topic 10	0.015	-0.004	-0.004	0.000	0.004	0.004	0.004	0.008
seen trend demand	(0.010)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.004)*
Topic 12	0.018	0.018	0.018	0.015	0.021	0.021	0.021	0.017
global market supply	(0.008)**	(0.008)**	(0.008)**	(0.006)**	(0.007)***	(0.007)***	(0.007)***	(0.006)***
Topic 13	0.03	0.032	0.028	0.003	0.031	0.033	0.03	0.002
unit confidence visibility	(0.013)**	(0.013)**	(0.013)**	(0.010)	(0.013)**	(0.013)**	(0.013)**	(0.011)
Topic 32	-0.04	-0.037	-0.038	-0.006	-0.039	-0.036	-0.036	-0.003
margin segment improvment	(0.01)***	(0.01)***	(0.01)***	(0.007)	(0.009)***	(0.009)***	(0.009)***	(0.006)
$AnaTone$		-0.862	-0.491	-0.462		-1.143	-0.758	-0.751
		(0.361)**	(0.342)	(0.271)*		(0.35)***	(0.338)**	(0.262)***
Executive sentiment		-0.925	-0.809	-0.557		-0.767	-0.624	-0.462
		(0.472)*	(0.483)*	(0.294)*		(0.473)	(0.479)	(0.284)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	13851	13851	13851	13851	13853	13853	13853	13853
$Adj.R^2$	0.031	0.035	0.033	0.022	0.035	0.039	0.038	0.027
Effects	none	none	year	Ind	none	none	year	Ind

Note: Clustered standard errors. $ln\Delta Put^{30}$ and $ln\Delta Call^{30}$ denotes the log of the contemporaneous change in ATM IV for puts and calls with 30 days maturities respectively. *, **, and *** indicate significance at the 10%, 5% and 1% critical level, respectively.

Table D.3: Puts and calls with 30 days maturity, Topics from executive answers and tones, 6-digit industry effects

	$ln\Delta Put^{30}$			$ln\Delta Call^{30}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Const	-0.154	-0.216	-0.059	-0.131	-0.201	-0.019
	(0.098)	(0.1)**	(0.116)	(0.099)	(0.102)**	(0.117)
Topic 7	-0.02	-0.021	-0.018	-0.019	-0.019	-0.017
product client launch	(0.006)***	(0.006)***	(0.006)***	(0.008)**	(0.008)**	(0.006)***
Topic 8	0.057	0.055	0.013	0.055	0.053	0.009
large deal transaction	(0.009)***	(0.009)***	(0.008)	(0.01)***	(0.01)***	(0.009)
Topic 20	-0.005	-0.003	-0.007	-0.006	-0.003	-0.005
opportunity investment capital	(0.004)	(0.004)	(0.003)**	(0.004)	(0.004)	(0.003)
Topic 31	-0.014	-0.017	-0.000	-0.012	-0.015	-0.000
europe china market	(0.006)**	(0.006)***	(0.005)	(0.006)*	(0.006)**	(0.005)
Topic 35	-0.016	-0.012	-0.006	-0.015	-0.01	-0.005
expect strong performance	(0.004)***	(0.004)***	(0.003)*	(0.004)***	(0.004)***	(0.003)
$AnaTone$		-0.533	-0.395		-0.805	-0.671
		(0.313)*	(0.268)		(0.301)***	(0.26)**
$ExeTone$		-0.443	-0.340		-0.421	-0.379
		(0.400)	(0.292)		(0.392)	(0.276)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs	13805	13805	13805	13805	13805	13805
Adj. R^2	0.066	0.066	0.031	0.063	0.065	0.032
Effects	none	year	Ind	none	year	Ind

Note: Clustered standard errors. $ln\Delta Put^{30}$ and $ln\Delta Call^{30}$ denotes the log of the contemporaneous change in ATM IV for puts and calls with 30 days maturities respectively. *, **, and *** indicate significance at the 10%, 5% and 1% critical level, respectively.

Table D.4: Spreads with 30, 60 and 90 days maturity, Topics from executive answers and tones, 6-digit industry effects

	$spread^{30}$		$spread^{60}$		$spread^{90}$	
	(1)	(2)	(3)	(4)	(5)	(6)
	Analyst Questions					
Const	0.095	0.089	0.106	0.099	0.129	0.121
	(0.055)*	(0.055)	(0.049)**	(0.049)**	(0.036)***	(0.036)***
Topic 9	-0.003	-0.003	-0.005	-0.005	-0.004	-0.004
plan update timing	(0.002)*	(0.002)*	(0.002)**	(0.002)**	(0.002)**	(0.002)**
Analyst sentiment		-0.191		-0.249		-0.35
		(0.128)		(0.134)*		(0.142)**
Controls	pd return (+)	pd return (+)	pd return (+)	pd return (-)	pd return (+)	pd return (+)
	return (-)	return (-)	return (-)	return (-)	mv log (-)	mv log (-)
			mv log (-)			
Obs	13889	13889	13938	13938	13948	13948
$Adj.R^2$	0.003	0.004	0.007	0.007	0.006	0.007
	Executive Answers					
Const	0.071	0.068	0.09	0.087	0.116	0.112
	(0.053)	(0.054)	(0.049)*	(0.049)*	(0.035)***	(0.036)***
Topic 15	-0.006	-0.006	-0.004	-0.004	-0.004	-0.004
opportunity store focus	(0.003)*	(0.003)*	(0.002)**	(0.002)**	(0.002)**	(0.002)**
Topic 35	-0.005	-0.005	-0.004	-0.004	-0.003	-0.003
expect strong performance	(0.002)**	(0.002)**	(0.002)***	(0.002)**	(0.002)*	(0.002)
Topic 36			-0.004	-0.004		
market share competitor			(0.002)**	(0.002)**		
AnaTone		-0.232		-0.244		-0.325
		(0.135)*		(0.136)*		(0.139)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs	13841	13841	13891	13891	13902	13902
$Adj.R^2$	0.004	0.004	0.007	0.008	0.006	0.007
Effects	Ind	Ind	Ind	Ind	Ind	Ind

Note: Clustered standard errors. $spread^M$ denotes ATM IV spread with $M = 30, 60$, and 90 days maturities. *, **, and *** indicate significance at the 10%, 5% and 1% critical level, respectively. Industry effects specification for all regressions.