

**When More Means Less: Economic Policy Uncertainty and the Informational Quality of
Forward-Looking Disclosure**

Ekene S. Aguegbah

Department of Applied Economics

Auburn University

Uchenna C. Onuoha

College of Business

California State University Long Beach

Poojan Patel

College of Business

Bryant University

Abstract

Economic policy uncertainty (EPU) increases investors' demand for forward-looking information while simultaneously increasing managers' incentives to avoid precise commitments. We examine how EPU influences both the quantity and informational quality of forward-looking disclosure in the MD&A section of 10-K filings. Using the Li (2010) dictionary approach and the Huang et al. (2023) FinBERT-FLS model, we analyze disclosure volume, specificity, year-over-year modification, and tone. We find that higher EPU is associated with increased forward-looking disclosure volume, but this increase masks important deterioration in quality. Managers substitute specific forward-looking statements with qualitative, non-specific language, increasingly recycle prior-year content rather than providing substantive updates, and adopt a more pessimistic tone. These findings indicate that heightened policy uncertainty encourages managers to preserve the appearance of forward-looking transparency while reducing the specificity, novelty, and informativeness of their disclosures.

Keywords: Economic Policy Uncertainty, Forward-Looking Statements, Voluntary Disclosure, Textual Analysis, MD&A, Disclosure Tone, FinBERT

JEL Codes: G38, D81, M41

Introduction

Economic Policy Uncertainty (EPU) measures the degree to which firms, investors, and policymakers are uncertain about who will set economic policy, what that policy will be, and when it will change, creating ambiguity regarding how firms should respond when the rules governing future economic activity become less predictable (Baker *et al.*, 2016). Consequently, a large body of literature documents that EPU shapes corporate investment, financing, mergers and acquisitions, divestitures, hiring, and dividend policy (Gulen & Ion, 2016; Bonaime *et al.*, 2018; D’Mello & Toscano, 2020; Jory *et al.*, 2020; Attig *et al.*, 2021; Frye *et al.*, 2024; Nguyen & Sila, 2025). Recent evidence further shows that EPU extends beyond firm-level real decisions into financial markets more broadly, reducing market pricing of future earnings, amplifying bond market volatility across global economies, distorting lending volumes and rates in peer-to-peer markets, generating measurable fiscal costs through its effects on public procurement, and transmitting financial stress shocks across regional and global markets (Drake *et al.*, 2018; Gong *et al.*, 2023; Zhou *et al.*, 2024; Leite, 2025; Rao *et al.*, 2026). Collectively, this evidence suggests that EPU not only changes firms’ economic decisions but also increases uncertainty surrounding firms’ future prospects, thereby increasing investors’ demand for credible firm-specific information. Yet, while prior research has extensively examined how EPU shapes both corporate decisions and capital market outcomes, they tell us considerably less about how managers adjust their disclosure behavior in response to heightened policy uncertainty. Voluntary disclosure is one of the primary mechanisms through which managers can reduce (or potentially widen) the information asymmetry between firms and outside investors, making it a natural setting in which to examine how firms respond when policy uncertainty rises. As the rules governing future economic activity become harder to forecast, investors face an increasing need for the forward-looking information needed to assess firms’ future prospects, even as managers face mounting pressure to avoid committing to

statements that may quickly prove inaccurate (Kaviani *et al.*, 2020). Whether managers respond to this tension is therefore not just a question of disclosure quantity, but of whether the credibility and informativeness of corporate communication itself deteriorate under heightened policy uncertainty (Jiang *et al.*, 2022). We revisit this question by examining how EPU influences managers' voluntary disclosure in the Management Discussion and Analysis (MD&A) section of annual 10-K filings retrieved from the U.S. Securities and Exchange Commission (SEC) EDGAR database. We focus on U.S. public firms because policy uncertainty has recently reached historically elevated levels (Londono *et al.*, 2025), and the SEC encourages managers to discuss known trends, uncertainties, and future expectations in the MD&A, allowing us to observe how managers adjust forward-looking disclosures when policy uncertainty rises.

Voluntary disclosure plays a central role in capital markets because it represents one of the primary channels through which managers communicate private information to outside investors. A large body of research shows that voluntary disclosures improve market liquidity, facilitate price discovery, and enhance investors' ability to assess firm value and future performance (Diamond & Verrecchia, 1991; Lang & Lundholm, 1996; Welker, 1995; Botosan, 1997; Leuz & Verrecchia, 2000; Healy & Palepu, 2001; Beyer *et al.*, 2010; Balakrishnan *et al.*, 2014). Other studies document that disclosure choices vary with the firm's investor base as shifts in investor clientele and information demand lead managers to adjust both the quantity and nature of voluntary disclosures (Bird & Karolyi, 2016; Vincenzi, 2025). Voluntary disclosure theory provides a natural framework for thinking about what managers are willing to disclose in the face of growing uncertainty. Whether managers disclose more, disclose differently, or retreat into the safety of prior-period language is therefore not simply a matter of discretion, but a function of how EPU reshapes the incentives underlying that discretion. Prior research establishes that managers weigh

the benefit of reducing investor information asymmetry against the costs of disclosure, including litigation exposure, proprietary information risk, and the hazard of committing to statements that subsequent events may render inaccurate (Verrecchia, 1983; Diamond & Verrecchia, 1991; Skinner, 1994; Healy & Palepu, 2001; Graham *et al.*, 2005; Verrecchia & Weber, 2006; Houston *et al.*, 2010; Rogers *et al.*, 2011). Under normal conditions, this trade-off produces a predictable equilibrium in which managers disclose when the benefits of communicating private information outweigh the associated costs. EPU, however, disrupts this equilibrium by pushing both sides of the trade-off simultaneously. On the demand side, rising policy uncertainty widens the information gap between managers and investors, as investors have less basis for forming expectations about future cash flows, capital allocation, and regulatory exposure, which intensifies their demand for forward-looking guidance (Nagar *et al.*, 2019). On the cost side, EPU raises the stakes of commitment: forward-looking statements issued under elevated policy uncertainty carry heightened litigation risk if the policy environment shifts and stated expectations prove materially inaccurate, and managers face greater proprietary risk from publicly committing to strategies whose viability depends on unresolved policy outcomes (Graham *et al.*, 2005; Verrecchia & Weber, 2006; Houston *et al.*, 2010; Rogers *et al.*, 2011). Because these two forces that elevate the demand for disclosure and the cost of providing it operate in opposing directions, the effect of EPU on voluntary forward-looking disclosure is theoretically ambiguous.

Existing empirical evidence provides only a partial understanding of how managers resolve this tradeoff. Bozanic *et al.* (2018) provide some of the earliest evidence that uncertainty changes the composition of forward-looking disclosure by documenting that managers substitute away from forecast-like earnings guidance toward other forms of forward-looking communication when uncertainty is high. Their findings broaden the measurement of forward-looking disclosure by

demonstrating that focusing solely on earnings forecasts provides an incomplete picture of firms' forward-looking disclosure decisions. Building on this broader view of forward-looking disclosure, recent studies examine how economic policy uncertainty shapes managers' disclosure decisions. Nagar *et al.* (2019) provide an important economic explanation by showing that economic policy uncertainty increases investor information asymmetry, leading managers to increase voluntary disclosure, although the additional disclosure only partially offsets the resulting increase in bid-ask spreads. Building on this insight, Jung and Kim (2024) show that managers provide more extensive forward-looking disclosures during periods of elevated policy uncertainty, while Jiang *et al.* (2022) document that these disclosures become longer, less readable, and increasingly uncertain and negative. Collectively, these studies suggest that policy uncertainty affects both the quantity and the broad textual characteristics of corporate disclosure. However, despite documenting changes in disclosure volume and broad textual characteristics, prior studies provide limited evidence on whether managers substantively update the content of forward-looking disclosures or simply expand existing narratives. In this study, we exploit firm-year variation in the Baker *et al.* (2016) news-based EPU index to examine both the volume and modification of forward-looking disclosure in the MD&A, allowing us to investigate whether managers respond to heightened policy uncertainty by substantively updating forward-looking language or instead relying on previously disclosed narratives. We extend Jung and Kim (2024) and Jiang *et al.* (2022), who examined how EPU affects disclosure volume and textual characteristics, by using a length-adjusted modification measure that directly captures whether forward-looking language is substantively updated year over year. Building on Bozanic *et al.* (2018), who demonstrate that focusing solely on earnings forecasts understates firms' overall

forward-looking disclosure, we show that even aggregate measures of forward-looking disclosure can mask important changes in its informational content.

To identify forward-looking disclosure, we employ two complementary methods: the Li (2010) keyword approach and the Huang et al. (2023) FinBERT-FLS model. We apply both methods to the MD&A section of annual 10-K filings because SEC Regulation S-K, Item 303 requires managers to discuss known trends, uncertainties, and future expectations, making the MD&A the primary source of narrative forward-looking disclosure in mandatory filings. This setting allows us to examine how economic policy uncertainty influences three distinct dimensions of forward-looking disclosure. Specifically, we examine whether EPU affects the volume of forward-looking information managers provide, the extent to which managers substantively update rather than recycle prior-period forward-looking language, and the tone of forward-looking communication. To operationalize these dimensions, we construct complementary measures of disclosure volume, substantive year-over-year modification, and tone. Disclosure volume is captured using sentence-level counts of specific and non-specific forward-looking statements, substantive modification using a length-adjusted year-over-year revision measure (Brown & Tucker, 2011; Thomas et al., 2024), and tone using a sentiment-based measure of forward-looking language.

Our results reveal that economic policy uncertainty (EPU) significantly changes both the quantity and quality of firms' forward-looking disclosure. First, EPU is associated with a significant increase in the volume of forward-looking statements in the MD&A, with elasticity estimates of 0.136 under the Li (2010) approach and 0.135 under the Huang et al. (2023) approach. This indicates a 10% increase in EPU is associated with approximately a 1.4% increase in forward-looking statements. However, this aggregate increase masks an important compositional shift: specific forward-looking statements decline by 0.6% for every 10% increase in EPU (coefficient

= -0.062), while non-specific forward-looking statements increase by 2.2% (coefficient = 0.221), suggesting that managers substitute qualitative, low-commitment language for more precise and verifiable guidance. Second, EPU significantly reduces the informativeness of forward-looking disclosure by lowering the extent to which managers substantively update forward-looking narratives. The length-adjusted modification score declines by 0.035 to 0.042 across the two identification approaches, indicating that managers increasingly recycle prior-year forward-looking language rather than updating investors with substantively new information. Third, EPU is associated with significantly more pessimistic forward-looking disclosure, reducing overall forward-looking tone by 0.035 to 0.044 points. This shift is driven almost entirely by non-specific forward-looking statements, whose tone declines by 0.038 points, whereas the tone of specific forward-looking statements remains statistically unchanged. At the sentence level, positive specific forward-looking sentences decline by 0.5% per 10% increase in EPU (coefficient = -0.051), while negative non-specific forward-looking sentences increase by 2.5% (coefficient = 0.250), indicating that managers respond to policy uncertainty by withdrawing concrete, optimistic guidance and expanding qualitative, pessimistic language. Collectively, these findings suggest that heightened economic policy uncertainty encourages managers to preserve the appearance of forward-looking transparency by increasing disclosure volume while simultaneously reducing the specificity, informational novelty, and optimism of the information they provide.

This paper makes three contributions. First, we extend the voluntary disclosure literature by showing that economic policy uncertainty affects not only the quantity but also the informational quality of forward-looking disclosure. Although firms disclose more forward-looking information under heightened policy uncertainty, the additional disclosure becomes increasingly non-specific, more repetitive, and more pessimistic. These findings demonstrate that greater disclosure volume

does not necessarily imply more informative disclosure or lower information asymmetry, particularly when investors have the greatest demand for forward-looking information. Second, we contribute to the economic policy uncertainty literature by identifying corporate narrative disclosure as an important channel through which policy uncertainty shapes firm behavior. Whereas prior studies focus on real corporate decisions such as investment, mergers and acquisitions, and innovation, we show that policy uncertainty also influences how managers communicate future prospects by encouraging more qualitative, less informative, and more pessimistic forward-looking disclosures. Third, we contribute methodologically by proposing a multidimensional framework for evaluating forward-looking disclosure that jointly considers disclosure quantity, specificity, substantive updating, and tone. This framework demonstrates that aggregate disclosure measures can obscure economically meaningful changes in the informational content of corporate narratives.

The rest of the paper is organized as follows. Section 2.0 describes the data and variables used for the analysis. Section 3.0 focuses on the empirical methodology employed in the study. Section 4.0 discusses the results, while Section 5.0 draws conclusions based on the outcomes of the study.

2.0 Data & Methodology

2.1 Sample construction

Our sample consists of U.S. firms with 10-K filings available on the SEC's EDGAR database between 1994 and 2024. We begin with the content of 10-K filings and extract the Management's Discussion and Analysis (MD&A) (Item 7) section from each filing using standardized parsing rules (Li, 2010; Brown & Tucker 2011; Thomas et al, 2024). We then merge the MD&A text with firm-level financial data from the COMPUSTAT Fundamentals Annual dataset, stock return and

liquidity data from CRSP, management forecast data from LSEG IBES Management Guidance, and macroeconomic uncertainty measures from publicly available sources described below. Following prior literature, we require non-missing total assets exceeding \$1 million and an average daily closing price exceeding \$1 to exclude penny stocks and shell entities. Our sample excludes regulated utilities (SIC 4900-4950) and financial firms (SIC 6000-6999). All continuous variables are winsorized at the 1st and 99th percentiles to reduce the influence of outliers.

2.2 Measuring Forward-Looking Statements Count, Modification, and Tone.

We construct three sets of forward-looking statement (FLS) measures from the MD&A text: modification, volume, and tone. To validate our findings across measurement approaches, we apply a dual-method identification strategy for FLS in 10-K filings, using Li’s (2010) rule-based detector and the Huang *et al.* (2023) FinBERT-FLS classifier.

The Li (2010) approach identifies a sentence as forward-looking if it contains any of a predefined set of future-oriented verbs (will, should, can, could, may, might, expect, anticipate, believe, plan, hope, intend, seek, project, forecast, objective, goal) and does not match a set of exclusion criteria for past-tense and legal-boilerplate language. The Huang *et al.* (2023) FinBERT-FLS approach uses a fine-tuned transformer model pretrained on financial text to classify each sentence as a specific FLS (sentences that contain quantifiable, concrete forward-looking content), a non-specific FLS (sentences that are qualitative or contain general forward-looking content), or a non-FLS. The combination of a rule-based detector and a machine-learning classifier allows us to validate our findings across measurement approaches.

We measure the volume of forward-looking disclosure as the total count of FLS sentences in the MD&A. $\ln(\text{CountFLS})$ (Li) is the natural log of the total number of FLS sentences identified by the

Li (2010) detector. $\ln(\text{CountFLS})$ (Huang *et al*) is the natural log of the total number of FLS sentences identified by FinBERT-FLS, which we further decompose into specific and non-specific FLS counts ($\ln(\text{CountSpecificFLS})$ (Huang *et al*) and $\ln(\text{CountNon-SpecificFLS})$ (Huang *et al*)) to capture variation in the precision of forward-looking content.

Next, we measure Forward-Looking Statement (FLS) Modification (FL_Modify) (Raw) as a proxy for the voluntary disclosure of new information, forward-looking information. We employ the Vector Space Model (VSM) approach of Salton *et al.* (1975) to measure year-over-year modifications in forward-looking MD&A disclosures. This approach, implemented by Brown and Tucker (2011) and Thomas *et al.* (2024), enables us to quantify the degree of year-over-year revision in a firm's disclosure content. The VSM treats each disclosure as a vector of weighted word frequencies, enabling a comparison of disclosure similarity across years. We measure the similarity between a firm's disclosure in year t and its disclosure in year $t-1$ by calculating the cosine of the angle between their respective TF-IDF vectors:

$$\text{SimilarityScore} = \cos(\theta) = \frac{v_1}{\|v_1\|} \cdot \frac{v_2}{\|v_2\|} = \frac{v_1 \cdot v_2}{\|v_1 v_2\|} \quad (1)$$

With $v_1 = (\alpha_1, \alpha_2, \dots, \alpha_{n-1}, \alpha_n)$ and $v_2 = (\beta_1, \beta_2, \dots, \beta_{n-1}, \beta_n)$

Here v_1 contains the n words in the forward-looking sentences in the MD&A disclosures in year t , and v_2 contains the n words in the forward-looking sentences in the MD&A disclosures issued by the same firm in year $t-1$. α and β count the frequency of each word in the two forward-looking MD&A disclosures. A similarity score close to 1 indicates that the disclosures in years t and $t-1$ are very similar. A score close to zero indicates both disclosures are unrelated. We define our primary measure of disclosure revision, FL_Modify (Raw), following Thomas *et al.* (2024) as one minus the similarity score. This value captures the degree of update in the forward-looking content from one year to the next. A higher value of FL_Modify (Raw) indicates a greater year-over-year

change in the forward-looking information disclosed and is interpreted as evidence of more informative or responsive forward-looking disclosure.

Following Brown and Tucker (2011) and Thomas *et al.* (2024), we adjust the *FL_Modify (Raw)* variable for disclosure length to avoid bias due to document size, since longer disclosures are more likely to contain overlapping content by chance. Specifically, we use a Taylor expansion at zero to empirically estimate the functional form of the relationship between the raw *FL_Modify (Raw)* score and MD&A disclosure length. The raw score measures the extent to which the current year's MD&A differs from the prior year, while length is defined as the number of words in the current year's MD&A. We regress the *FL_Modify (Raw)* measure on the first five polynomials of document length and use the fitted values from this regression as the expected modification score conditional on disclosure length. This adjusted measure, which we term *FL_Modify*, is calculated as the raw score minus the fitted score from this regression. By removing this influence of document size, the adjusted *FL_Modify* more accurately reflects substantive changes in disclosure content.

Next, we measure the tone of forward-looking statements using the FinBERT-tone model (Huang *et al.*, 2023), which classifies each FLS sentence as Positive, Neutral, or Negative. Tone is computed as the average sentiment score across all FLS sentences in the MD&A in year t , defined as the difference between the counts of positive and negative FLS sentences, divided by the total number of FLS sentences (including neutral sentences). Higher (lower) values indicate more positive (negative) forward-looking sentiment. We construct tone measures separately for FLS identified by the Li (2010) detector (*Tone FLS Li*) and FinBERT-FLS (*Tone FLS Huang*), and we decompose the FinBERT-FLS tone into specific and non-specific components.

2.3 Measuring Economic Policy Uncertainty (EPU)

Our primary measure of economic policy uncertainty is the Baker, Bloom, and Davis (2016) news-based EPU index. This news-based component captures the volume of newspaper coverage referencing policy uncertainty in ten major U.S. newspapers. For each firm-year, we compute the average EPU over the prior 12 months ending on the firm's fiscal year-end reporting date and use the natural logarithm of this average ($LN(EPU)$) as our main regressor following a methodology similar to Gulen & Ion (2016).

To isolate the effect of economic policy-specific uncertainty from general macroeconomic uncertainty, we also control for broad macroeconomic uncertainty using the Jurado *et al.* (2015) one-year-ahead macroeconomic uncertainty index (JLNUM12M), which captures the conditional volatility of the unpredictable component of a broad set of macroeconomic and financial time series. Including this measure in our specifications allows us to interpret the EPU coefficient as the effect of economic policy-specific uncertainty over and above general macroeconomic uncertainty.

3.0 Empirical Specification

To examine the effect of EPU on forward-looking disclosure, we estimate the following firm-year-level panel regression:

$$Y_{i,t} = \beta_1 LN(EPU)_{i,t} + \gamma' X_{i,t} + \delta M_t + \alpha_i + \epsilon_{i,t} \quad (2)$$

where $Y_{i,t}$ is one of our FLS measures (modification, volume, or tone) for firm i in fiscal year t , $LN(EPU)_{i,t}$ is the natural logarithm of the firm-year average EPU index, $X_{i,t}$ the vector of firm-level forward-looking statement controls following Brown & Tucker (2011) and Thomas *et al.* (2024), M_t is the vector of macroeconomic controls, and α_i are firm fixed effects that absorb time-invariant firm-level heterogeneity.

Following Brown and Tucker (2011) and Thomas *et al.* (2024), we include a comprehensive set of firm-level controls designed to capture economic changes that may independently influence the volume, substantive updating, and tone of forward-looking disclosure in the MD&A. Specifically, we control for changes in operating performance using the absolute year-over-year change in diluted earnings per share scaled by the fiscal-year-end stock price (*AbsChgEPS*), as operating performance is a primary driver of MD&A revisions. To account for changes in firms' financial condition, we include the absolute change in the current ratio (*AbsChgCurrentRatio*), the absolute change in debt due within one year scaled by total assets (*AbsChgDebtDue*), the absolute change in total leverage scaled by total assets (*AbsChgLeverage*), and the absolute change in free cash flow scaled by total assets (*AbsChgFCF*), which collectively capture changes in liquidity, capital structure, and financing needs. We further control for changes in firms' external operating environment by including the absolute change in stock return volatility (*AbsChgStdReturn*) as a proxy for market risk exposure and the absolute change in stock liquidity (*AbsChgStockLiquidity*) to capture shifts in market liquidity that may influence voluntary disclosure incentives. To account for major organizational changes that naturally require revisions to corporate disclosure, we include indicator variables for substantial asset decreases of at least one-third (*Downsize*) and substantial asset increases of at least one-third (*Acquire*), which proxy for significant divestiture and acquisition activity. Finally, we control for firm characteristics that may systematically influence disclosure practices. These include firm size (*Size*), measured as the natural logarithm of total assets; audit quality, captured by an indicator for Big 6 auditors (*Big6*); industry concentration, measured using the Herfindahl-Hirschman Index at the two-digit SIC level (*HHI*) to capture proprietary disclosure incentives; and the number of Form 8-K filings during the fiscal year (*Num8kfilings*), which proxies for the complexity of the firm's information environment.

Our baseline specifications include firm fixed effects and standard errors clustered at the firm level but exclude year fixed effects. We omit year fixed effects because EPU is a macroeconomic time-series variable that exhibits minimal cross-sectional variation within a given period. Including year fixed effects would therefore absorb nearly all of the identifying variation in EPU, leaving little variation with which to estimate its effect¹. Instead of year fixed effects, we control for time-varying macroeconomic conditions using a vector of macroeconomic variables commonly employed in the EPU literature. These include real GDP growth, GDP forecast dispersion and a presidential election year indicator (Gulen & Ion, 2016; Duong *et al.*, 2020; Xu, 2020); investor sentiment (Baker & Wurgler, 2007; Xu, 2020); broad macroeconomic uncertainty (Jurado *et al.*, 2015); and an indicator for NBER recession years (Nguyen *et al.*, 2017; Duong *et al.*, 2020). Collectively, these controls account for changes in the broader economic environment while preserving the time-series variation in EPU that identifies our coefficient of interest. Standard errors are clustered at the firm level to account for arbitrary within-firm serial correlation in the residuals, consistent with the baseline specification in Xu (2020) and Duong *et al.* (2020).

Our coefficient of interest is β_1 which captures the within-firm association between economic policy uncertainty and forward-looking disclosure after controlling for firm characteristics and macroeconomic conditions. The interpretation of β_1 depends on the disclosure outcome under consideration. For disclosure volume, a positive β_1 indicates that firms provide more forward-looking information under elevated policy uncertainty. For substantive updating, a positive β_1 indicates greater revision of prior-year forward-looking disclosures. For tone, a positive β_1

¹ This concern is well established in EPU literature. Gulen and Ion (2016) note that because many firms have fiscal quarters ending at the same time, there is only trivial cross-sectional variation in EPU within a given period, and they emphasize that including time fixed effects would mechanically absorb the explanatory power of the policy uncertainty variable. Nguyen & Phan (2017), Bonaime *et al.*, (2018), Xu (2020), and Duong *et al.*, (2020) reach the same conclusion and omit year fixed effects from their EPU specifications.

indicates more optimistic forward-looking communication. Conversely, a negative β_1 coefficient indicates lower disclosure volume, greater reliance on previously disclosed forward-looking narratives, or more pessimistic forward-looking communication, depending on the disclosure outcome being examined. Because economic policy uncertainty simultaneously increases investors' demand for forward-looking information while increasing managers' costs of providing credible forward-looking disclosures, voluntary disclosure theory does not make an unambiguous prediction regarding the sign of β_1 .

[Insert Table 1]

Table 1 reports descriptive statistics for the sample. On average, firms disclose approximately 50 forward-looking statements in the MD&A under the Li (2010) approach and 48 under the FinBERT-FLS approach, of which roughly 15 are specific FLS and 33 are non-specific. The mean raw modification score (*FLS_Modify_Raw*) is 0.182 (Li, 2010) approach and 0.192 (Huang *et al.*, 2023), indicating that firms revise approximately 19% of the information content of their forward-looking statements from one year to the next, on average, while the overall tone of forward-looking disclosure is mildly negative across both identification approaches, with sentiment scores of -0.083 (Li, 2010) and -0.098 (Huang *et al.*, 2023). These statistics indicate meaningful variation in the volume, substantive updating, and tone of forward-looking disclosure, providing ample variation for the empirical analyses. Detailed variable definitions are reported in Appendix Table A.

4.0 Results and Discussion

4.1 FLS Sentence Count, Modification, Tone, and Economic Policy Uncertainty.

We organize our empirical analysis around three dimensions of forward-looking disclosure: volume, modification, and tone. Together, these measures allow us to assess not only whether managers provide more forward-looking statements under elevated economic policy uncertainty, but also whether that content is substantively different relative to prior-year language and how the sentiment embedded in the disclosure shifts as uncertainty rises.

[Insert Table 2]

We begin with the volume of forward-looking disclosure. Voluntary disclosure theory holds that managers disclose private information when the benefits of reducing investor information asymmetry outweigh the costs of disclosure (Verrecchia, 1983; Healy & Palepu, 2001). On the demand side, a widening of the information gap between managers and investors raises the benefit of disclosure and should, all else equal, induce managers to supply more forward-looking information (Diamond & Verrecchia, 1991). Nagar *et al.* (2019) apply this logic to economic policy uncertainty, showing that EPU widens information asymmetry and that managers respond by increasing voluntary disclosure. Table 2 provides support for this prediction at the aggregate level. EPU is positively and significantly associated with the number of forward-looking sentences in the MD&A, with coefficient estimates of 0.136 ($t = 6.402$) under the Li (2010) approach and 0.135 ($t = 6.202$) under the Huang *et al.* (2023) FinBERT-FLS approach to detecting FLS (Columns 1 and 2). Because both the dependent variable and EPU are in logarithmic form, these coefficients have an elasticity interpretation: a 10% increase in EPU is associated with approximately a 1.4% increase in the number of forward-looking sentences in the MD&A. This result corroborates and extends Jung and Kim (2024), who document a positive association between EPU and forward-looking language in narrative R&D disclosures, by showing that the effect generalizes to the full MD&A section and holds across both identification approaches.

The aggregate increase in forward-looking disclosure masks an important compositional shift. Columns (3) and (4) decompose total forward-looking statements into specific and non-specific disclosures using the Huang et al. (2023) FinBERT-FLS classifier. EPU is negatively associated with specific forward-looking statements (coefficient = -0.062, $t = -3.054$) but positively associated with non-specific forward-looking statements (coefficient = 0.221, $t = 10.375$). Economically, a 10% increase in EPU is associated with approximately a 0.6% decline in specific forward-looking statements and a 2.2% increase in non-specific forward-looking statements. These indicate that the increase in overall forward-looking disclosure is driven entirely by an expansion of qualitative, low-commitment language, while managers simultaneously reduce more precise and verifiable forward-looking communication. This pattern is consistent with voluntary disclosure theory. As policy uncertainty increases, the expected costs of issuing specific forward-looking commitments (including forecast error and litigation risk) rise relative to the informational benefits of disclosure. Managers therefore preserve the appearance of transparency by increasing the quantity of forward-looking discussion while shifting away from disclosures that require more precise commitments. This substitution extends the evidence in Bozanic et al. (2018) from firm-specific uncertainty to aggregate policy uncertainty, suggesting that managers respond to both sources of uncertainty by replacing specific forward-looking disclosure with more qualitative communication.

[Insert Table 3]

If the volume results suggest that managers expand the quantity of forward-looking text while withdrawing from specific commitments, the modification results reveal whether the text they provide includes new information. The voluntary disclosure framework holds that informative disclosure requires managers to update their disclosures in response to new information about the firm's prospects and operating environment (Brown & Tucker, 2011; Thomas et al., 2024). If EPU

induces managers to provide more useful guidance, forward-looking content will become more, not less, distinct from the prior year. Table 3 shows the latter. The coefficient on $LN(EPU)$ is negative and highly significant across all four specifications, with estimates of -0.035 ($t = -9.480$) and -0.042 ($t = -10.404$) for the length-adjusted FL_Modify measure under the Li (2010) and Huang et al. (2023) FinBERT-FLS approaches (Columns 1 and 2), and -0.035 ($t = -9.551$) and -0.043 ($t = -10.567$) for the raw modification scores with MD&A length controlled directly (Columns 3 and 4). An increase in log EPU is associated with a decline in the modification score of approximately 0.035 to 0.043 units, indicating that managers reduce the modification of the information content of year-over-year forward-looking statements as uncertainty rises. The near-identical estimates across the length-adjusted and unadjusted specifications confirm that the result is not an artifact of variation in document length across the EPU distribution, and the consistency across the two FLS identification approaches indicates that the finding does not depend on how forward-looking sentences are identified. Under elevated policy uncertainty, managers recycle more of their prior-year forward-looking language rather than revising it to reflect new information about the firm's prospects or the evolving policy environment.

Read alongside the volume decomposition, the modification results present a picture of voluntary disclosure that appears expansive but is static in substance. Managers issue more forward-looking statements that are largely reconstituted from the prior year's filing, substituting the familiar language of prior-period guidance for the substantive updates that investors most need when the policy environment is more volatile. The control variables reinforce this explanation. Acquisition activity is positively and significantly associated with FL_Modify across all specifications, consistent with the intuition that major corporate events compel managers to revise their forward-looking language to reflect changed business conditions (Brown & Tucker, 2011). Firm size is

negatively associated, reflecting the tendency of larger, more established firms to revise their disclosures less, given their more diversified information environment. The recession indicator enters positively and significantly, indicating that macroeconomic contractions do compel forward-looking updates even where EPU alone does not. This divergence between the recession and EPU coefficients is itself informative: recessions represent realized shocks to firm fundamentals that force disclosure updates, whereas EPU represents unresolved uncertainty that instead induces managers to hedge through language recycling and qualitative substitution rather than substantive revision. In this respect, our findings extend those of Jiang *et al.* (2022), who document that EPU increases disclosure length while reducing readability by showing that the degradation in disclosure quality includes forward-looking content, a dimension that length and readability measures do not capture.

[Insert Table 4]

Having established that managers expand qualitative FLS volume while recycling prior-period language under heightened uncertainty, we turn to the sentiment they embed in those disclosures. The tone of forward-looking disclosure carries informational value independent of its volume and year-over-year modification. Prior literature shows that the sentiment embedded in corporate filings is associated with market outcomes and that measuring it requires finance-specific classification of tone (Loughran & McDonald, 2011), and that investors react to the tone of MD&A disclosure, which carries information beyond quantitative measures such as earnings surprises and accruals (Feldman *et al.*, 2010). Table 4, Panel A, shows that EPU is associated with more negative forward-looking disclosure tone, with coefficient estimates of -0.035 ($t = -11.273$) under the Li (2010) approach and -0.044 ($t = -13.671$) under the Huang et al. (2023) FinBERT-FLS approach (Columns 1 and 2). Forward-looking language in the MD&A thus becomes meaningfully more

pessimistic as policy uncertainty rises. The decomposition in Columns (3) and (4) reveals that this pessimism is not distributed uniformly. The tone of specific FLS is statistically indistinguishable from zero (Column 3), whereas the tone of non-specific FLS is negative and highly significant at -0.038 ($t = -10.877$) (Column 4). Managers do not meaningfully alter the sentiment of their concrete, quantifiable forward-looking commitments given increasing policy uncertainty. Instead, they concentrate negative sentiment in the qualitative, hedged type of their forward-looking language, the segment that carries the least litigation risk and imposes the lowest commitment cost.

The sentence-level decomposition in Panels B, C, and D identifies the precise channels through which this aggregate tone shift operates. Panel B shows that EPU is associated with a significant decline in positive tone specific FLS sentences, with a coefficient of -0.051 ($t = -3.194$), indicating that a 10% increase in EPU is associated with a 0.5% decline in the number of positive specific forward-looking sentences, whereas the coefficient on positive non-specific counts is statistically insignificant. Managers selectively withdraw optimistic, concrete guidance as EPU rises, while leaving their positive qualitative language unchanged. Panel C shows that EPU is associated with an overall increase in negative forward-looking sentences, with coefficients of 0.225 ($t = 12.023$) under the Li (2010) approach and 0.217 ($t = 11.537$) under the Huang et al. (2023) approach, indicating that a 10% increase in EPU is associated with approximately a 2.2% increase in the number of negative forward-looking sentences. The decomposition reveals that this increase is driven by non-specific FLS, with a coefficient of 0.250 ($t = 13.429$), while negative specific FLS sentences decline slightly, with a coefficient of -0.031 ($t = -2.842$). This again points to the non-specific channel as the primary vehicle through which managers embed pessimism into their forward-looking disclosures. Panel D shows that EPU is associated with a significant increase in neutral forward-looking sentences in aggregate, with coefficients of 0.109 ($t = 5.248$) under the Li

(2010) approach and 0.110 ($t = 5.165$) under the Huang et al. (2023) approach. The decomposition reveals the same compositional pattern documented where neutral specific FLS decline significantly at -0.069 ($t = -3.596$), indicating that a 10% increase in EPU is associated with a 0.7% decline in neutral specific forward-looking sentences, while neutral non-specific FLS increase at 0.175 ($t = 8.450$), indicating that the same 10% increase is associated with a 1.8% increase in neutral non-specific forward-looking sentences. The aggregate increase in neutral sentences is therefore driven entirely by the non-specific segment, consistent with the compositional rotation from specific to non-specific content documented across all sentiment categories.

Taken together, the tone results describe a pattern of asymmetric sentiment management. Under elevated EPU, specific forward-looking sentences decline across all three sentiment categories (positive, negative, and neutral), indicating a broad withdrawal from concrete, verifiable forward-looking commitments regardless of their directional content. The expansion in forward-looking language is concentrated entirely in non-specific sentences, where negative and neutral non-specific FLS increase substantially while positive non-specific FLS remain unchanged. The net effect is a disclosure posture that conveys increased pessimism through the low-cost, low-commitment channel while systematically reducing the provision of specific forward-looking information across the entire sentiment spectrum. This behavior is consistent with the commitment-hazard mechanism documented in the disclosure literature: managers avoid specific forward-looking statements when the risk of ex post inaccuracy is elevated (Graham *et al.*, 2005; Houston *et al.*, 2010). While the overall tone of forward-looking disclosure is negatively associated with EPU, the withdrawal of positive, specific forward-looking statements, in particular, is consistent with Rogers et al. (2011), which shows that an optimistic disclosure tone significantly increases shareholder litigation risk. Under elevated policy uncertainty, where the likelihood that

stated expectations will prove inaccurate is higher, the litigation cost of optimistic, verifiable forward-looking commitments rises accordingly, providing managers with a direct incentive to withdraw precisely these statements while channeling any residual forward-looking discussion through the non-specific, qualitative segment that is harder to verify and therefore less likely to serve as the basis for a shareholder complaint.

4.2 Robustness Tests

4.21. Corroborating Evidence from Management Earnings Guidance

The results in the preceding sections establish that elevated EPU is associated with a systematic deterioration in the informational content of forward-looking disclosure in the MD&A given increasing policy uncertainty: managers produce more forward-looking sentences that have less new information content and have more negative sentiment, with the deterioration concentrated in the qualitative, non-specific segment of the forward-looking content. A logical next question is whether this pattern of managerial retreat from informative forward-looking disclosure extends beyond the MD&A to other voluntary disclosure channels. To examine this, we turn to management earnings guidance, which provides a direct, revealed-preference measure of managerial willingness to commit to forward-looking information. Unlike MD&A disclosure, which is embedded in a mandatory annual filing and subject to boilerplate tendencies, management earnings guidance is a fully discretionary act where managers choose whether to issue a forecast, how frequently to do so, and how far in advance of the fiscal year-end to provide it. If EPU induces a retreat from informative forward-looking commitment, we expect both a reduction in the frequency of earnings guidance and a contraction in the horizon over which managers are willing to commit to forward-looking earnings figures.

[Insert Table 5]

The results in Table 5 confirm both predictions. The coefficient on $LN(EPU)$ for guidance frequency is negative and significant at -1.075 ($t = -12.625$), indicating that managers issue significantly fewer earnings forecasts as EPU rises. The coefficient on $LN(EPU)$ for guidance horizon is likewise negative and significant at -11.260 ($t = -2.559$), indicating that when managers do issue guidance under elevated EPU, they issue it later. These effects are economically meaningful. Both represent a material reduction in the forward-looking information available to investors through this discretionary guidance channel.

The consistency of these findings with the MD&A evidence is notable because the two sets of results are derived from independent data sources and capture managerial behavior through different disclosure mechanisms. EPU reduces the substantive information content and precision of forward-looking language in mandatory MD&A filings, and simultaneously reduces the frequency and lead time of discretionary earnings guidance. Taken together, these patterns point to a common underlying mechanism that suggests that when the policy environment becomes harder to forecast, managers retreat from forward-looking commitment across both mandatory and discretionary channels.

Our finding that annual EPS guidance frequency declines under EPU is consistent with Lee *et al.* (2026), who decompose management forecasts by type and show that EPS guidance frequency is negatively associated with EPU when examined separately from other forecast categories. Their decomposition confirms that the retreat from forward-looking commitment under policy uncertainty is concentrated in the most commitment-intensive forecast type (EPS), precisely the pattern our results document. This evidence also complements the broader disclosure findings of

Nagar *et al.* (2019), who report that prior-quarter EPU is positively associated with the aggregate frequency of management forecasts and voluntary 8-K filings in the following quarter, and that these additional disclosures only partially offset the resulting rise in information asymmetry. Their design differs from ours in two respects: they examine a near-term lead relation at quarterly frequency, and their forecast measure aggregates all forecast types, including capital expenditure, sales, and EPS, alongside voluntary 8-K filings such as Regulation FD releases and press releases. That managers increase near-term, broadly defined disclosure frequency, as Nagar *et al.* (2019) document, while curtailing annual EPS commitments specifically, as both our results and Lee *et al.* (2026) find, is consistent with the substitution we observe within the MD&A between specific and non-specific FLS, where managers shift away from specific, quantifiable forward-looking statements toward qualitative, low-commitment language. Across both the MD&A and the guidance channel, the common pattern is a retreat from precise, high-commitment forward-looking disclosure under elevated policy uncertainty, even as the overall volume of disclosure rises.

4.2.2 Forward-Looking Disclosure Around Crisis Periods

The results presented thus far establish the average within-firm effect of EPU on forward-looking disclosure over the full 1994 to 2024 sample period. A complementary question is whether the disclosure response to uncertainty is uniform across episodes of elevated uncertainty or whether the nature of the shock shapes how managers adjust their forward-looking communication. Crisis periods are informative in this regard because they generate sharp, concentrated increases in uncertainty of all types over short windows, allowing us to examine disclosure behavior in a tightly bounded event-study design that complements the continuous EPU specification in our main analysis. Table 6 reports three separate event studies covering the DotCom crisis (Panel A, 1998 to 2003), the Global Financial Crisis (Panel B, 2005 to 2010), and the COVID-19 pandemic (Panel

C, 2017 to 2022), each comparing forward-looking disclosure in the three years preceding the crisis to the three crisis years.

[Insert Table 6]

The evidence across the three episodes reveals a heterogeneity that is both statistically and economically informative. During the DotCom crisis, Panel A shows that managers significantly increased the volume of forward-looking disclosure, with coefficients on the DotCom indicator of 0.236 ($t = 7.167$) under the Li (2010) approach and 0.264 ($t = 7.649$) under the Huang et al. (2023) FinBERT-FLS approach for log total FLS count, indicating that forward-looking sentence counts were approximately 27% to 30% higher during the crisis years than in the pre-crisis period. The decomposition reveals significant increases in both specific FLS at 0.111 ($t = 3.638$), corresponding to roughly a 12% increase, and non-specific FLS at 0.363 ($t = 10.531$), corresponding to roughly a 44% increase, indicating that the volume expansion was heavily skewed toward qualitative, non-specific forward-looking content. The modification measure, by contrast, is statistically insignificant under the Li (2010) approach and only marginally significant under the Huang *et al.* (2023) approach at 0.018 ($t = 2.264$). Managers thus produced substantially more forward-looking statements during the DotCom period than in the preceding three years, but they did not meaningfully update the substance of that content relative to prior-year language. This pattern mirrors our main results: a crisis-driven surge in forward-looking volume unaccompanied by a commensurate increase in informational novelty, with the additional forward-looking sentences skewed toward non-specific content at a ratio of roughly four to one over specific content.

The *Global Financial Crisis*, reported in Panel B, presents a different picture. In contrast to the *DotCom* and COVID periods, the Financial Crisis indicator is associated with a significant decrease in the modification of forward-looking disclosure, with coefficients of -0.022 ($t = -3.859$) under the Li (2010) approach and -0.019 ($t = -3.298$) under the Huang et al. (2023) approach, indicating that managers reduce prior-year forward-looking disclosure modification during the crisis years than in the pre-crisis period. At the same time, total FLS increased significantly, with coefficients of 0.071 ($t = 2.966$) under the Li (2010) approach and 0.066 ($t = 2.626$) under Huang et al. (2023), corresponding to approximately a 7% increase in forward-looking sentences during the crisis years. The decomposition reveals that this increase was driven entirely by non-specific FLS at 0.093 ($t = 3.876$), corresponding to roughly a 10% increase, while specific FLS was statistically unchanged at -0.006 ($t = -0.265$). The Financial Crisis thus produced a more pronounced version of the disclosure pattern than the *DotCom* period where managers expanded qualitative, non-specific forward-looking language while simultaneously reducing modification of prior-year content, combining a volume increase with a modification decline that represents the starkest divergence between disclosure quantity and disclosure quality. The result is consistent with the commitment-hazard mechanism emphasized in the disclosure literature (Graham et al., 2005; Houston et al., 2010).

The COVID-19 pandemic results in Panel C align more closely with the *DotCom* pattern than with the Financial Crisis on the modification dimension, but diverge from both episodes on the composition of the volume increase. Total FLS volume increases significantly, with coefficients of 0.200 ($t = 4.834$) under the Li (2010) approach and 0.197 ($t = 4.547$) under the Huang et al. (2023) approach, corresponding to approximately a 22% increase in forward-looking sentences during the pandemic years relative to the pre-crisis period. The modification measure is statistically

insignificant under both identification approaches (0.004, $t = 0.381$ and 0.006, $t = 0.544$), replicating the DotCom pattern of expanded volume without substantive updating. Where COVID diverges from both prior episodes is in the composition of the volume increase. The decomposition shows that specific FLS increased by 0.186 ($t = 4.115$), corresponding to roughly a 20% increase, and non-specific FLS increased by 0.191 ($t = 4.421$), corresponding to roughly a 21% increase. Unlike the DotCom crisis, where non-specific FLS expanded at roughly four times the rate of specific FLS, and unlike the Financial Crisis, where only non-specific FLS expanded, the COVID volume increase was distributed nearly equally across both segments. This balanced expansion may reflect the unprecedented nature of the pandemic shock and the associated investor demand for concrete operational guidance on business continuity, supply-chain exposure, and liquidity management, which drew managers into providing specific forward-looking content at rates comparable to their non-specific expansion, even as the substance of their disclosure remained largely unmodified from prior-year language.

Taken together, the crisis-period evidence reinforces and extends our primary EPU results. All three episodes produced significant increases in the volume of forward-looking disclosure, though the composition of that increase varied: the DotCom expansion was heavily skewed toward non-specific FLS, the Financial Crisis expansion was driven entirely by non-specific FLS with no increase in specific content, and the COVID expansion was distributed nearly equally across both segments. On the modification dimension, the results are broadly consistent. The Financial Crisis is the only episode that produced a significant decline in modification across both identification approaches. The COVID period showed no significant change in modification under either approach. The DotCom results are mixed: modification is insignificant under the Li (2010) approach (0.010, $t = 1.302$) but marginally positive under the Huang *et al.* (2023) approach (0.018,

$t = 2.264$), suggesting a modest increase in forward-looking revision that is not robust across identification methods. Critically, none of the three crisis periods produced a large or consistent increase in the substantive novelty of forward-looking content relative to the significant volume expansions documented in each episode. The Financial Crisis represents the most pronounced version of this pattern, as it is the only episode in which volume expanded while modification simultaneously declined. This consistency across three distinct crisis episodes, each differing in origin, severity, and duration, reinforces the central finding of our continuous EPU analysis that the informational content of forward-looking disclosure does not increase in proportion to its volume, and the conditions under which managers produce the most forward-looking text are frequently those in which the substantive quality of that text is least likely to improve.

4.2.3 MD&A Tone Validation Using Loughran-McDonald Dictionary Measures

Our primary tone results rely on the FinBERT-tone classifier, which evaluates sentiment at the sentence level. To assess whether these findings are sensitive to the measurement approach, we re-examine MD&A tone using the Loughran and McDonald (LM) (2011) finance-specific word lists, which classify individual words into negative, positive, uncertainty, and complexity categories. This test applies a fundamentally different measurement methodology to the same underlying text: a dictionary-based word-count approach rather than a context-aware sentence-level classifier. Because word counts are mechanically related to document length, we include the natural logarithm of MD&A word count as an additional control in all specifications to ensure that the coefficients capture compositional shifts in language rather than a mechanical length effect.

[Insert Table 7]

Table 7 reports the results. Because both the dependent variables and EPU are in logarithmic form, the coefficients have an elasticity interpretation. After controlling for MD&A length, EPU is positively and significantly associated with LM negative words (coefficient = 0.143, $t = 16.343$) and LM uncertainty words (coefficient = 0.115, $t = 13.042$), indicating that a 10% increase in EPU is associated with approximately a 1.4% increase in negative words and a 1.2% increase in uncertainty words in the MD&A. EPU is also positively and significantly associated with LM complexity words (coefficient = 0.085, $t = 7.405$), indicating that the MD&A becomes more linguistically complex as policy uncertainty rises. In contrast, EPU is negatively and significantly associated with LM positive words (coefficient = -0.030, $t = -3.600$), indicating that a 10% increase in EPU is associated with a 0.3% decline in positive language, holding document length constant. This pattern of increased negative, uncertain, and complex language alongside reduced positive language is consistent with the sentence-level decomposition in Table 4, where the tone shift operates through a combination of increased negative, non-specific, forward-looking sentences and reduced positive, specific, forward-looking statements. The LM uncertainty result is particularly informative, as it provides direct lexical evidence that managers embed more uncertainty-related language in the MD&A when the policy environment is most uncertain, reinforcing the connection between the Baker *et al.* (2016) EPU index and the actual language managers choose in their filings. The convergence across the two measurement approaches, one classifying sentiment at the forward-looking statement sentence level and the other counting individual words from a finance-specific dictionary, increases our confidence that the shift toward more negatively toned disclosure under EPU reflects a substantive change in managerial communication rather than a measurement artifact.

Conclusion

This study examines how economic policy uncertainty (EPU) influences the volume, modification, and tone of forward-looking disclosure in the Management Discussion and Analysis (MD&A) section of firms' annual 10-K filings. Drawing on voluntary disclosure theory, we argue that heightened policy uncertainty simultaneously increases investors' demand for forward-looking information while raising managers' costs of providing credible forward-looking commitments. Using both the Li (2010) keyword approach and the Huang et al. (2023) FinBERT-FLS classifier to identify forward-looking statements, we show that EPU fundamentally changes not only how much managers disclose, but also the nature of what they disclose.

Our findings reveal that although managers provide more forward-looking statements as policy uncertainty increases, the additional disclosure is driven primarily by non-specific, qualitative language rather than concrete and verifiable guidance. At the same time, managers increasingly recycle prior-year forward-looking disclosures instead of providing substantive updates and adopt a more pessimistic tone by concentrating negative sentiment within non-specific statements. Taken together, our findings suggest that managers respond to heightened policy uncertainty by preserving disclosure flexibility rather than increasing disclosure informativeness. Consequently, greater disclosure volume during periods of elevated policy uncertainty should not be interpreted as evidence of greater transparency. Consequently, increases in forward-looking disclosure volume should not be interpreted as evidence of greater transparency, particularly during periods when investors face the greatest policy uncertainty.

These findings have important implications for investors, analysts, regulators, and researchers. For investors and analysts, greater forward-looking disclosure during periods of elevated policy uncertainty may overstate the amount of decision-useful information available because much of

the additional disclosure consists of recycled, qualitative, and low-commitment language. For regulators, our findings suggest that disclosure quality cannot be adequately assessed using aggregate disclosure measures such as document length or statement counts alone. Instead, evaluating the specificity, novelty, and sentiment of forward-looking disclosures provides a more complete assessment of the information available to capital market participants.

As with any empirical study, our findings are subject to several limitations. First, EPU is a macroeconomic variable with limited cross-sectional variation within a given period, which means our identification relies primarily on time-series variation in EPU after controlling for firm fixed effects and observable macroeconomic conditions. Although this approach is standard in the EPU literature (Gulen & Ion, 2016; Nagar *et al.*, 2019) and we employ multiple robustness tests including alternative uncertainty proxies, crisis-period event studies, and cross-sectional moderator analyses, we cannot fully rule out the possibility that unobserved time-varying factors correlated with both EPU and disclosure behavior influence our results. However, reverse causality is unlikely in our setting, because EPU is determined by aggregate government policy actions that individual firms cannot meaningfully influence (Nagar *et al.*, 2019), and disclosure decisions by any single firm are implausible drivers of national policy uncertainty. Second, following established practice in the EPU literature, our specifications include firm fixed effects but not year fixed effects because EPU varies primarily over time rather than across firms within a given period, and year fixed effects would absorb the variation that identifies our coefficient of interest. While we explicitly control for macroeconomic conditions, we acknowledge that this approach cannot replicate the within-year identification that year fixed effects would provide. Third, our sample is restricted to U.S. firms that file 10-K annual reports with the SEC, and our textual analysis depends on our parsing algorithm's ability to accurately extract the MD&A section (Item 7) from these

filings. To the extent that parsing errors introduce noise into our forward-looking statement measures, our estimates may be attenuated. More broadly, the extent to which our findings generalize to other institutional settings with different disclosure regimes, litigation environments, or levels of policy uncertainty remains an open question. Although our use of firm fixed effects, dual identification methods, and extensive robustness tests mitigates many of these concerns, we cannot fully rule out the influence of unobserved heterogeneity.

Our analysis also points to several directions for future research. While we focus on U.S. publicly traded firms and the MD&A section of annual 10-K filings, future studies could examine whether similar disclosure patterns persist in other disclosure outlets, such as earnings press releases and in international markets facing different regulatory environments. Future research could also focus on the demand side of disclosure to investigate whether investors, analysts, and credit rating agencies recognize the decline in the informational quality of forward-looking disclosures under heightened policy uncertainty and incorporate these changes into their valuation and forecasting decisions. Our findings suggest that periods characterized by the greatest demand for forward-looking information may also be those in which the informational quality of forward-looking disclosure deteriorates most sharply. Understanding this distinction is essential for interpreting corporate disclosure under heightened policy uncertainty.

REFERENCES

- Ali, A., Klasa, S., & Yeung, E. (2014). Industry concentration and corporate disclosure policy. *Journal of Accounting and Economics*, 2013 Conference Issue, 58(2), 240–264. <https://doi.org/10.1016/j.jacceco.2014.08.004>
- Attig, N., El Ghouli, S., Guedhami, O., & Zheng, X. (2021). Dividends and economic policy uncertainty: International evidence. *Journal of Corporate Finance*, 66, 101785. <https://doi.org/10.1016/j.jcorpfin.2020.101785>
- Baker, M., & Wurgler, J. (2006). Investor Sentiment and the Cross-Section of Stock Returns. *The Journal of Finance*, 61(4), 1645–1680. <https://doi.org/10.1111/j.1540-6261.2006.00885.x>
- Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring Economic Policy Uncertainty. *The Quarterly Journal of Economics*, 131(4), 1593–1636. <https://doi.org/10.1093/qje/qjw024>
- Balakrishnan, K., Billings, M. B., Kelly, B., & Ljungqvist, A. (2014). Shaping Liquidity: On the Causal Effects of Voluntary Disclosure. *The Journal of Finance*, 69(5), 2237–2278. <https://doi.org/10.1111/jofi.12180>
- Ball, R., Jayaraman, S., & Shivakumar, L. (2012). Audited financial reporting and voluntary disclosure as complements: A test of the Confirmation Hypothesis. *Journal of Accounting and Economics*, 53(1), 136–166. <https://doi.org/10.1016/j.jacceco.2011.11.005>
- Beyer, A., Cohen, D. A., Lys, T. Z., & Walther, B. R. (2010). The financial reporting environment: Review of the recent literature. *Journal of Accounting and Economics*, 50(2), 296–343. <https://doi.org/10.1016/j.jacceco.2010.10.003>
- Bird, A., & Karolyi, S. A. (2016). Do Institutional Investors Demand Public Disclosure? *The Review of Financial Studies*, 29(12), 3245–3277. <https://doi.org/10.1093/rfs/hhw062>
- Bonaime, A., Gulen, H., & Ion, M. (2018). Does policy uncertainty affect mergers and acquisitions? *Journal of Financial Economics*, 129(3), 531–558. <https://doi.org/10.1016/j.jfineco.2018.05.007>
- Botosan, C. A. (1997). Disclosure Level and the Cost of Equity Capital. *The Accounting Review*, 72(3), 323–349.
- Bozanic, Z., Roulstone, D. T., & Van Buskirk, A. (2018). Management earnings forecasts and other forward-looking statements. *Journal of Accounting and Economics*, 65(1), 1–20. <https://doi.org/10.1016/j.jacceco.2017.11.008>
- Brown, S. V., & Tucker, J. W. (2011). Large-Sample Evidence on Firms' Year-over-Year MD&A Modifications. *Journal of Accounting Research*, 49(2), 309–346.
- Clarkson, P. M., Ferguson, C., & Hall, J. (2003). Auditor conservatism and voluntary disclosure: Evidence from the Year 2000 systems issue. *Accounting and Finance*, 43(1), 21–40.

- Diamond, D. W., & Verrecchia, R. E. (1991). Disclosure, Liquidity, and the Cost of Capital. *The Journal of Finance*, 46(4), 1325–1359. <https://doi.org/10.1111/j.1540-6261.1991.tb04620.x>
- D’Mello, R., & Toscano, F. (2020). Economic policy uncertainty and short-term financing: The case of trade credit. *Journal of Corporate Finance*, 64, 101686. <https://doi.org/10.1016/j.jcorpfin.2020.101686>
- Drake, M. S., Mayberry, M. A., & Wilde, J. H. (2018). Pushing the future back: The impact of policy uncertainty on the market pricing of future earnings. *Journal of Business Finance & Accounting*, 45(7–8), 895–927. <https://doi.org/10.1111/jbfa.12316>
- Duong, H. N., Nguyen, J. H., Nguyen, M., & Rhee, S. G. (2020). Navigating through economic policy uncertainty: The role of corporate cash holdings. *Journal of Corporate Finance*, 62, 101607. <https://doi.org/10.1016/j.jcorpfin.2020.101607>
- Feldman, R., Govindaraj, S., Livnat, J., & Segal, B. (2010). Management’s tone change, post earnings announcement drift and accruals. *Review of Accounting Studies*, 15(4), 915–953. <https://doi.org/10.1007/s11142-009-9111-x>
- Frye, M. B., Pham, D. T., & Whyte, A. M. (2024). Economic policy uncertainty and corporate divestitures. *Journal of Business Finance & Accounting*, 51(5–6), 1120–1160. <https://doi.org/10.1111/jbfa.12747>
- Gong, Y., Li, X., & Xue, W. (2023). The impact of EPU spillovers on the bond market volatility: Global evidence. *Finance Research Letters*, 55, 103931. <https://doi.org/10.1016/j.frl.2023.103931>
- Graham, J. R., Harvey, C. R., & Rajgopal, S. (2005). The economic implications of corporate financial reporting. *Journal of Accounting and Economics*, 40(1), 3–73. <https://doi.org/10.1016/j.jacceco.2005.01.002>
- Gulen, H., & Ion, M. (2016). Policy Uncertainty and Corporate Investment. *The Review of Financial Studies*, 29(3), 523–564.
- Harris, M. S. (1998). The Association between Competition and Managers’ Business Segment Reporting Decisions. *Journal of Accounting Research*, 36(1), 111–128. <https://doi.org/10.2307/2491323>
- Healy, P. M., & Palepu, K. G. (1993). The Effect of Firms’ Financial Disclosure Strategies on Stock Prices. *Accounting Horizons*, 7(1), 1–11. <https://doi.org/10.2308/AH-9603204645>
- Healy, P. M., & Palepu, K. G. (2001). Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature. *Journal of Accounting and Economics*, 31(1), 405–440. [https://doi.org/10.1016/S0165-4101\(01\)00018-0](https://doi.org/10.1016/S0165-4101(01)00018-0)

- Houston, J. F., Lev, B., & Tucker, J. W. (2010). To Guide or Not to Guide? Causes and Consequences of Stopping Quarterly Earnings Guidance. *Contemporary Accounting Research*, 27(1), 143–185. <https://doi.org/10.1111/j.1911-3846.2010.01005.x>
- Huang, A. H., Wang, H., & Yang, Y. (2023). FinBERT: A Large Language Model for Extracting Information from Financial Text. *Contemporary Accounting Research*, 40(2), 806–841. <https://doi.org/10.1111/1911-3846.12832>
- Jiang, L., Pittman, J. A., & Saffar, W. (2022). Policy Uncertainty and Textual Disclosure. *Accounting Horizons*, 36(4), 113–131. <https://doi.org/10.2308/HORIZONS-2019-515>
- Jory, S. R., Khieu, H. D., Ngo, T. N., & Phan, H. V. (2020). The influence of economic policy uncertainty on corporate trade credit and firm value. *Journal of Corporate Finance*, 64, 101671. <https://doi.org/10.1016/j.jcorpfin.2020.101671>
- Jung, K., & Kim, S. (2024). Economic policy uncertainty and narrative R&D disclosures. *Finance Research Letters*, 70, 106290. <https://doi.org/10.1016/j.frl.2024.106290>
- Jurado, K., Ludvigson, S. C., & Ng, S. (2015). Measuring Uncertainty. *American Economic Review*, 105(3), 1177–1216. <https://doi.org/10.1257/aer.20131193>
- Kaviani, M. S., Kryzanowski, L., Maleki, H., & Savor, P. (2020). Policy uncertainty and corporate credit spreads. *Journal of Financial Economics*, 138(3), 838–865. <https://doi.org/10.1016/j.jfineco.2020.07.001>
- Lang, M. H., & Lundholm, R. J. (1996). Corporate Disclosure Policy and Analyst Behavior. *The Accounting Review*, 71(4), 467–492.
- Lee, R., Thompson, M. A., & Williams, C. D. (2026). Policy Uncertainty and Corporate Voluntary Disclosure. *Journal of Financial Reporting*, 11(1), 117–141. <https://doi.org/10.2308/JFR-2023-012>
- Leite, R. (2025). The public cost of economic policy uncertainty: Evidence from brazilian public procurements. *Finance Research Letters*, 86, 108665. <https://doi.org/10.1016/j.frl.2025.108665>
- Leuz, C., & Verrecchia, R. E. (2000). The Economic Consequences of Increased Disclosure. *Journal of Accounting Research*, 38, 91–124. <https://doi.org/10.2307/2672910>
- Li, F. (2010). The Information Content of Forward-Looking Statements in Corporate Filings—A Naïve Bayesian Machine Learning Approach. *Journal of Accounting Research*, 48(5), 1049–1102. <https://doi.org/10.1111/j.1475-679X.2010.00382.x>
- Londono, J. M., Ma, S., & Wilson, B. A. (2025). Costs of Rising Uncertainty. *FEDS Notes*. <https://www.federalreserve.gov/econres/notes/feds-notes/costs-of-rising-uncertainty-20250424.html>

- Nagar, V., Schoenfeld, J., & Wellman, L. (2019). The effect of economic policy uncertainty on investor information asymmetry and management disclosures. *Journal of Accounting and Economics*, 67(1), 36–57. <https://doi.org/10.1016/j.jacceco.2018.08.011>
- Nguyen, D. D., & Sila, V. (2025). Corporate Hiring under Uncertainty. *The Review of Corporate Finance Studies*, 14(4), 949–988. <https://doi.org/10.1093/rcfs/cfaf008>
- Nguyen, N. H., & Phan, H. V. (2017). Policy Uncertainty and Mergers and Acquisitions. *The Journal of Financial and Quantitative Analysis*, 52(2), 613–644.
- Pástor, L., & Veronesi, P. (2012). Uncertainty about Government Policy and Stock Prices. *The Journal of Finance*, 67(4), 1219–1264. <https://doi.org/10.1111/j.1540-6261.2012.01746.x>
- Rao, A., Bindabel, W., Dagar, V., & Guesmi, K. (2026). US financial stress, regional spillovers, and global economic policy uncertainty. *Finance Research Letters*, 89, 109168. <https://doi.org/10.1016/j.frl.2025.109168>
- Rogers, J. L., Van Buskirk, A., & Zechman, S. L. C. (2011). Disclosure Tone and Shareholder Litigation. *The Accounting Review*, 86(6), 2155–2183.
- Salton, G., Wong, A., & Yang, C. S. (1975). A vector space model for automatic indexing. *Communications of the ACM*, 18(11), 613–620. <https://doi.org/10.1145/361219.361220>
- Skinner, D. J. (1994). Why Firms Voluntarily Disclose Bad News. *Journal of Accounting Research*, 32(1), 38–60. <https://doi.org/10.2307/2491386>
- Thomas, W. B., Wang, Y., & Zhang, L. (2024). Algorithmic Trading and Forward-Looking MD&A Disclosures. *Journal of Accounting Research*, 62(4), 1533–1569. <https://doi.org/10.1111/1475-679X.12540>
- Verrecchia, R. E. (1983). Discretionary disclosure. *Journal of Accounting and Economics*, 5, 179–194. [https://doi.org/10.1016/0165-4101\(83\)90011-3](https://doi.org/10.1016/0165-4101(83)90011-3)
- Verrecchia, R. E. (2001). Essays on disclosure. *Journal of Accounting and Economics*, 32(1), 97–180. [https://doi.org/10.1016/S0165-4101\(01\)00025-8](https://doi.org/10.1016/S0165-4101(01)00025-8)
- Verrecchia, R. E., & Weber, J. (2006). Redacted Disclosure. *Journal of Accounting Research*, 44(4), 791–814. <https://doi.org/10.1111/j.1475-679X.2006.00216.x>
- Welker, M. (1995). Disclosure Policy, Information Asymmetry, and Liquidity in Equity Markets. *Contemporary Accounting Research*, 11(2), 801–827. <https://doi.org/10.1111/j.1911-3846.1995.tb00467.x>
- Xu, Z. (2020). Economic policy uncertainty, cost of capital, and corporate innovation. *Journal of Banking & Finance*, 111, 105698. <https://doi.org/10.1016/j.jbankfin.2019.105698>

Zhou, F., Chang, A. (Jasmine), & Shi, J. (2024). How the Economic Policy Uncertainty (EPU) impacts FinTech: The implication of P2P lending markets. *Finance Research Letters*, 70, 106268. <https://doi.org/10.1016/j.frl.2024.106268>

TABLES

Table 1: Descriptive Statistics

	N	Mean	SD	p25	p50	p75
Panel A: FLS Count, FLS Modification and FLS Tone Samples						
FL_Modify (Raw) (Li)	62,932	0.182	0.221	0.046	0.098	0.219
FL_Modify (Raw) (Huang <i>et al</i>)	62,932	0.192	0.237	0.046	0.100	0.230
FL_Modify(Li)	62,932	-0.006	0.193	-0.100	-0.050	0.041
FL_Modify(Huang <i>et al</i>)	62,932	-0.007	0.205	-0.107	-0.052	0.046
Ln(CountFLS)(Li)	68,577	3.517	1.104	3.091	3.761	4.234
Ln(CountFLS)(Huang <i>et al</i>)	68,577	3.465	1.130	3.045	3.738	4.190
Ln(CountSpecificFLS)(Huang <i>et al</i>)	68,577	2.333	1.045	1.792	2.565	3.045
Ln(CountNon-SpecificFLS)(Huang <i>et al</i>)	68,577	3.061	1.157	2.565	3.367	3.829
Tone FLS (Li)	68,577	-0.083	0.169	-0.154	-0.056	0.000
Tone FLS (Huang <i>et al</i>)	68,577	-0.098	0.172	-0.167	-0.071	0.000
Tone Specific FLS (Huang <i>et al</i>)	68,577	0.132	0.197	0.000	0.087	0.250
Tone Non-Specific FLS (Huang <i>et al</i>)	68,577	-0.209	0.193	-0.290	-0.170	-0.074
Ln(PositiveCount) FLS (Li)	68,577	1.311	0.905	0.693	1.386	1.946
Ln(PositiveCount) FLS (Huang <i>et al</i>)	68,577	1.180	0.839	0.693	1.099	1.792
Ln(PositiveCount) Specific FLS (Huang <i>et al</i>)	68,577	1.016	0.808	0.000	1.099	1.609
Ln(PositiveCount) Non-Specific FLS (Huang <i>et al</i>)	68,577	0.383	0.511	0.000	0.000	0.693
Ln(NegativeCount FLS) (Li)	68,577	1.810	1.028	1.099	1.946	2.485
Ln(NegativeCount FLS) (Huang <i>et al</i>)	68,577	1.802	1.043	1.099	1.946	2.485
Ln(NegativeCount Specific) FLS (Huang <i>et al</i>)	68,577	0.451	0.587	0.000	0.000	0.693
Ln(NegativeCount Non-Specific FLS) (Huang <i>et al</i>)	68,577	1.692	1.038	1.099	1.792	2.398
Ln(NeutralCount FLS) (Li)	68,577	3.205	1.081	2.773	3.466	3.932
Ln(NeutralCount FLS) (Huang <i>et al</i>)	68,577	3.160	1.106	2.708	3.434	3.892
Ln(NeutralCount Specific FLS) (Huang <i>et al</i>)	68,577	2.052	1.000	1.609	2.197	2.773
Ln(NeutralCount Non-Specific FLS) (Huang <i>et al</i>)	68,577	2.765	1.129	2.197	3.091	3.555
LN(EPU)	68,577	4.800	0.354	4.506	4.857	5.025
LN(MDA_Length)	68,577	8.558	1.173	8.195	8.848	9.284
Ln(LM Negative)	68,577	3.961	1.222	3.466	4.190	4.762
Ln(LM Positive)	68,577	3.395	1.168	2.944	3.638	4.174
Ln(LM Uncertainty)	68,577	4.089	1.092	3.664	4.344	4.796

Ln(LM Complexity)	68,577	2.756	1.185	2.079	2.944	3.611
AbsChgStockLiquidity	68,577	0.585	0.558	0.189	0.418	0.800
AbsChgEPS	68,577	0.191	0.687	0.011	0.032	0.108
AbsChgCurrentRatio	68,577	1.104	2.317	0.132	0.361	0.981
AbsChgDebtDue	68,577	0.018	0.052	0.000	0.002	0.012
AbsChgLeverage	68,577	0.106	0.147	0.023	0.058	0.127
AbsChgFCF	68,577	0.085	0.118	0.019	0.047	0.103
AbsChgStdReturn	68,577	0.102	0.273	0.017	0.041	0.085
Downsize	68,577	0.042	0.200	0.000	0.000	0.000
Acquire	68,577	0.146	0.353	0.000	0.000	0.000
Size	68,577	5.990	1.978	4.531	5.886	7.348
Big6	68,577	0.873	0.333	1.000	1.000	1.000
Num8kfilings	68,577	8.869	6.733	3.000	9.000	13.000
Litigation	68,577	0.398	0.490	0.000	0.000	1.000
HHI	68,577	0.070	0.070	0.032	0.044	0.077
OANCF	68,577	0.013	0.238	-0.004	0.071	0.126
LeverageRatio	68,577	0.572	2.679	0.002	0.241	0.779
CurrentRatio	68,577	3.153	3.344	1.395	2.136	3.503
Recession	68,577	0.156	0.362	0.000	0.000	0.000
Presidential_election	68,577	0.239	0.427	0.000	0.000	0.000
Real GDP Growth	68,577	2.630	1.643	1.800	2.725	3.450
StockSentiment	68,577	0.186	0.663	-0.247	-0.016	0.413
JLN_MacroUncertainty	68,577	0.914	0.058	0.870	0.902	0.936
GDPDispersion	68,577	0.478	0.221	0.330	0.410	0.600
DotCom (2001-2003)	68,577	0.116	0.321	0.000	0.000	0.000
Financial Crisis (2008-2010).	68,577	0.097	0.295	0.000	0.000	0.000
COVID Period (2020-2022).	68,577	0.106	0.308	0.000	0.000	0.000

Panel B: Frequency and Horizon Sample

Freq_Guidance	13,850	4.128	2.283	2.000	4.000	5.000
Horizon_Guidance	13,850	313.436	118.245	305.000	323.000	338.000
Ln(MVE)	13,850	7.542	1.802	6.303	7.485	8.752
BTM	13,850	0.452	0.445	0.216	0.367	0.588
Leverage	13,850	0.233	0.194	0.067	0.220	0.349
RetVol	13,850	0.027	0.013	0.018	0.024	0.033
Beta	13,850	1.069	0.461	0.774	1.043	1.333
MeanTurn	13,850	0.009	0.007	0.005	0.007	0.011
Big4	13,850	0.889	0.314	1.000	1.000	1.000
Litigation	13,850	0.370	0.483	0.000	0.000	1.000
Change_EARN	13,850	0.007	0.100	-0.015	0.007	0.027
Loss	13,850	0.152	0.359	0.000	0.000	0.000
EarnVol	13,850	0.055	0.109	0.015	0.027	0.054
LN(EPU)	13,850	4.833	0.344	4.528	4.927	5.032
Recession	13,850	0.172	0.378	0.000	0.000	0.000
Presidential_election	13,850	0.238	0.426	0.000	0.000	0.000
Real GDP Growth	13,850	2.365	1.567	1.675	2.425	3.300
StockSentiment	13,850	0.080	0.654	-0.308	-0.131	0.163
JLN_MacroUncertainty	13,850	0.918	0.057	0.883	0.905	0.934
GDPDispersion	13,850	0.484	0.226	0.330	0.450	0.600

TABLE 2: Number of Forward-Looking Statements and Economic Policy Uncertainty (EPU)

VARIABLES	(1) Ln(CountFLS) (Li)	(2) Ln(CountFLS) (Huang <i>et al</i>)	(3) Ln(CountSpecificFLS) (Huang <i>et al</i>)	(4) Ln(CountNon-SpecificFLS) (Huang <i>et al</i>)
LN(EPU)	0.136*** [6.402]	0.135*** [6.202]	-0.062*** [-3.054]	0.221*** [10.375]
<u>Firm Controls</u>				
AbsChgStockLiquidity	0.024*** [3.559]	0.019*** [2.726]	0.014** [2.161]	0.022*** [3.100]
AbsChgEPS	0.016** [2.198]	0.011 [1.570]	0.007 [0.986]	0.014** [2.025]
AbsChgCurrentRatio	0.000 [0.262]	-0.000 [-0.067]	-0.001 [-0.334]	-0.000 [-0.181]
AbsChgDebtDue	0.024 [0.277]	0.025 [0.284]	0.125 [1.429]	-0.006 [-0.070]
AbsChgLeverage	-0.013 [-0.455]	-0.008 [-0.267]	0.061** [2.162]	-0.051* [-1.700]
AbsChgFCF	0.065* [1.731]	0.039 [1.003]	0.040 [1.083]	0.019 [0.481]
AbsChgStdReturn	-0.045*** [-2.883]	-0.051*** [-3.195]	-0.043*** [-2.882]	-0.048*** [-2.988]
Downsize	0.045** [2.408]	0.046** [2.415]	0.014 [0.736]	0.065*** [3.396]
Acquire	-0.054*** [-4.844]	-0.043*** [-3.777]	0.001 [0.122]	-0.070*** [-5.991]
Size	0.063*** [5.444]	0.063*** [5.453]	0.007 [0.642]	0.094*** [7.940]
Big6	-0.021 [-0.868]	-0.030 [-1.221]	0.042* [1.820]	-0.059** [-2.302]
Num8kfilings	0.020*** [16.088]	0.020*** [16.129]	0.009*** [7.892]	0.026*** [20.993]
HHI	0.215 [0.761]	0.129 [0.455]	-0.234 [-0.944]	0.346 [1.169]
<u>Economic Controls</u>				
Recession	0.037** [2.207]	0.045*** [2.613]	0.107*** [6.813]	0.035** [2.064]
Presidential_election	-0.070*** [-11.209]	-0.069*** [-10.618]	-0.017*** [-2.856]	-0.104*** [-15.764]
Real GDP Growth	-0.025*** [-8.655]	-0.032*** [-10.738]	-0.004 [-1.330]	-0.045*** [-14.871]
StockSentiment	-0.111*** [-17.035]	-0.103*** [-15.603]	-0.050*** [-7.997]	-0.128*** [-19.318]
JLN_MacroUncertainty	-0.328*** [-2.852]	-0.613*** [-5.141]	-0.690*** [-6.219]	-0.576*** [-4.886]

GDPDispersion	-0.054*** [-2.864]	-0.024 [-1.255]	0.032* [1.752]	-0.061*** [-3.120]
Observations	68,577	68,577	68,577	68,577
R-squared	0.532	0.527	0.524	0.544
Firm FE	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm

This table presents results from regressions of the log of forward-looking statement (FLS) sentence counts on Economic Policy Uncertainty (EPU). Columns (1) and (2) estimate OLS regression models for the total number of FLS sentences in the MD&A section of 10-K filings identified by the Li (2010) keyword approach and the Huang *et al.* (2023) FinBERT-FLS classifier, respectively. Columns (3) and (4) decompose the Huang *et al.* count into specific FLS sentences (containing concrete, quantifiable forward-looking content) and non-specific FLS sentences (containing qualitative or general forward-looking content). $LN(EPU)$ is the natural logarithm of the firm-year average of the Baker, Bloom, and Davis (2016) news-based Economic Policy Uncertainty index over the 12 months ending on the firm's fiscal year-end. All regressions include firm fixed effects. t-statistics are reported in brackets. Standard errors are clustered at the firm level. Variable definitions are provided in Appendix A. Continuous variables are winsorized at the 1st and 99th percentiles. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 3: Forward-Looking Statement Modification and Economic Policy Uncertainty (EPU)

VARIABLES	(1) FL_Modify (Li)	(2) FL_Modify (Huang <i>et al</i>)	(1) FL_Modify (Raw) (Li)	(2) FL_Modify (Raw) (Huang <i>et al</i>)
LN(EPU)	-0.035*** [-9.480]	-0.042*** [-10.404]	-0.035*** [-9.551]	-0.043*** [-10.567]
LN(MDA_Length)			-0.083*** [-34.153]	-0.091*** [-36.474]
<u>Firm Controls</u>				
AbsChgStockLiquidity	0.003** [2.032]	0.004** [2.343]	0.003** [2.275]	0.004*** [2.693]
AbsChgEPS	0.004*** [2.964]	0.004** [2.483]	0.005*** [3.249]	0.004*** [2.779]
AbsChgCurrentRatio	0.001*** [3.333]	0.001*** [3.383]	0.001*** [3.284]	0.001*** [3.313]
AbsChgDebtDue	0.054*** [3.011]	0.065*** [3.512]	0.055*** [3.035]	0.068*** [3.539]
AbsChgLeverage	0.029*** [4.672]	0.036*** [5.498]	0.030*** [4.757]	0.036*** [5.473]
AbsChgFCF	0.004 [0.488]	0.014* [1.700]	0.006 [0.757]	0.017** [2.018]
AbsChgStdReturn	0.003 [0.902]	0.005 [1.337]	0.004 [1.182]	0.006 [1.582]
Downsize	0.008* [1.886]	0.006 [1.331]	0.007* [1.740]	0.006 [1.271]
Acquire	0.027*** [11.107]	0.024*** [9.527]	0.028*** [11.348]	0.025*** [9.756]
Size	-0.011*** [-6.101]	-0.012*** [-6.080]	-0.011*** [-5.654]	-0.011*** [-5.537]
Big6	0.010** [2.290]	0.017*** [3.570]	0.013*** [2.890]	0.019*** [4.151]
Num8kfilings	-0.000 [-1.230]	-0.001*** [-2.745]	-0.000 [-1.565]	-0.001*** [-3.017]
HHI	-0.151*** [-3.128]	-0.136*** [-2.630]	-0.128*** [-2.757]	-0.110** [-2.164]
<u>Economic Controls</u>				
Recession	0.047*** [14.376]	0.057*** [16.036]	0.049*** [14.680]	0.059*** [16.411]
Presidential_election	0.003* [1.668]	0.001 [0.397]	0.004*** [2.805]	0.003* [1.801]
Real GDP Growth	0.005*** [7.814]	0.005*** [8.212]	0.005*** [8.126]	0.006*** [8.617]
StockSentiment	0.010*** [7.391]	0.011*** [7.915]	0.011*** [7.618]	0.012*** [8.187]
JLN_MacroUncertainty	-0.102*** [-4.531]	-0.119*** [-4.861]	-0.118*** [-5.143]	-0.138*** [-5.619]

GDPDispersion	0.003 [0.817]	0.002 [0.396]	0.000 [0.022]	-0.002 [-0.398]
Observations	62,932	62,932	62,932	62,932
R-squared	0.337	0.356	0.478	0.503
Firm FE	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm

This table presents results from regressions of forward-looking statement (FLS) modification scores on Economic Policy Uncertainty (EPU). Columns (1) and (2) estimate OLS regression models for the length-adjusted *FL_Modify* measure using FLS identified by the Li (2010) keyword approach and the Huang *et al.* (2023) FinBERT-FLS classifier, respectively. Columns (3) and (4) present robustness regressions using the raw (non-length-adjusted) *FL_Modify (Raw)* scores with the natural logarithm of MD&A word count included as a control. *LN(EPU)* is the natural logarithm of the firm-year average of the Baker, Bloom, and Davis (2016) news-based Economic Policy Uncertainty index over the 12 months ending on the firm's fiscal year-end. All regressions include firm fixed effects. t-statistics are reported in brackets. Standard errors are clustered at the firm level. Variable definitions are provided in Appendix A. Continuous variables are winsorized at the 1st and 99th percentiles. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Forward-Looking Statements Tone and Economic Policy Uncertainty (EPU)**Panel A: Forward-Looking Statements (FLS) Sentiment and Economic Policy Uncertainty (EPU)**

VARIABLES	(1) Tone FLS (Li)	(2) Tone FLS (Huang <i>et al</i>)	(3) Tone Specific FLS (Huang <i>et al</i>)	(4) Tone Non-Specific FLS (Huang <i>et al</i>)
LN(EPU)	-0.035*** [-11.273]	-0.044*** [-13.671]	0.005 [1.301]	-0.038*** [-10.877]
Observations	68,577	68,577	68,577	68,577
R-squared	0.469	0.463	0.406	0.433
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm

Panel A presents results from regressions of forward-looking statement (FLS) tone on Economic Policy Uncertainty (EPU). FLS tone is defined as the average sentiment score across all FLS sentences in the MD&A section of 10-K filings, where each sentence is classified by the FinBERT-tone model (Huang *et al.*, 2023) as Positive (+1), Neutral (0), or Negative (−1). Columns (1) and (2) present results for FLS sentences identified using the Li (2010) keyword approach and the Huang *et al.* (2023) FinBERT-FLS classifier, respectively. Columns (3) and (4) decompose the Huang *et al.* measure into specific FLS sentences (containing concrete, quantifiable forward-looking content) and non-specific FLS sentences (containing qualitative or general forward-looking content). All regressions include the full set of firm-level and macroeconomic controls reported in Table 2 (coefficients suppressed for brevity) and firm fixed effects. t-statistics are reported in brackets. Standard errors are clustered at the firm level. Variable definitions are provided in Appendix A. Continuous variables are winsorized at the 1st and 99th percentiles. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel B: Number of Positive Forward-Looking Statements (FLS) and Economic Policy Uncertainty (EPU)

VARIABLES	(1) Ln(PosCount FLS) (Li)	(2) Ln(PosCount FLS) (Huang <i>et al</i>)	(3) Ln(PosCount Specific) (Huang <i>et al</i>)	(4) Ln(PosCount Non- Specific) (Huang <i>et al</i>)
LN(EPU)	0.008 [0.456]	-0.036** [-2.199]	-0.051*** [-3.194]	0.007 [0.662]
Observations	68,577	68,577	68,577	68,577
R-squared	0.528	0.504	0.497	0.467
Controls	Yes	Yes	Yes	Yes

Firm FE Cluster	Yes Firm	Yes Firm	Yes Firm	Yes Firm
Panel B presents results from regressions of the log of the number of positive forward-looking statement (FLS) sentences on Economic Policy Uncertainty (EPU). The dependent variable is the count of FLS sentences in the MD&A section of 10-K filings classified as positive in tone by the FinBERT-tone model (Huang <i>et al.</i>, 2023). Columns (1) and (2) present results for FLS sentences identified using the Li (2010) keyword approach and the Huang <i>et al.</i> (2023) FinBERT-FLS classifier, respectively. Columns (3) and (4) decompose the Huang <i>et al.</i> measure into specific FLS sentences (containing concrete, quantifiable forward-looking content) and non-specific FLS sentences (containing qualitative or general forward-looking content). All regressions include the full set of firm-level and macroeconomic controls reported in Table 2 (coefficients suppressed for brevity) and firm fixed effects. t-statistics are reported in brackets. Standard errors are clustered at the firm level. Variable definitions are provided in Appendix A. Continuous variables are winsorized at the 1st and 99th percentiles. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.				

Panel C: Number of Negative Forward-Looking Statements (FLS) and Economic Policy Uncertainty (EPU)

VARIABLES	(1) Ln(NegCount FLS) (Li)	(2) Ln(NegCount FLS) (Huang <i>et al.</i>)	(3) Ln(NegCount Specific) (Huang <i>et al.</i>)	(4) Ln(NegCount Non-Specific) (Huang <i>et al.</i>)
LN(EPU)	0.225*** [12.023]	0.217*** [11.537]	-0.031*** [-2.842]	0.250*** [13.429]
Observations	68,577	68,577	68,577	68,577
R-squared	0.509	0.518	0.429	0.521
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm

Panel C presents results from regressions of the log of the number of negative forward-looking statements (FLSs) on Economic Policy Uncertainty (EPU). The dependent variable is the count of FLS sentences in the MD&A section of 10-K filings classified as negative in tone by the FinBERT-tone model (Huang *et al.*, 2023). Columns (1) and (2) present results for FLS sentences identified using the Li (2010) keyword approach and the Huang *et al.* (2023) FinBERT-FLS classifier, respectively. Columns (3) and (4) decompose the Huang *et al.* measure into specific FLS sentences (containing concrete, quantifiable forward-looking content) and non-specific FLS sentences (containing qualitative or general forward-looking content). All regressions include the full set of firm-level and macroeconomic controls reported in Table 2 (coefficients suppressed for brevity) and firm fixed effects. t-statistics are reported in brackets. Standard errors are clustered at the firm level. Variable definitions are provided in Appendix A. Continuous variables are winsorized at the 1st and 99th percentiles. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel D: Number of Neutral Forward-Looking Statements (FLS) and Economic Policy Uncertainty (EPU)

VARIABLES	(1) Ln(NeuCount FLS) (Li)	(2) Ln(NeuCount FLS) (Huang <i>et al</i>)	(3) Ln(NeuCount Specific) (Huang <i>et al</i>)	(4) Ln(NeuCount Non- Specific) (Huang <i>et al</i>)
LN(EPU)	0.109*** [5.248]	0.110*** [5.165]	-0.069*** [-3.596]	0.175*** [8.450]
Observations	68,577	68,577	68,577	68,577
R-squared	0.540	0.534	0.516	0.557
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm

Panel D presents results from regressions of the log of the number of neutral forward-looking statement (FLS) sentences on Economic Policy Uncertainty (EPU). The dependent variable is the count of FLS sentences in the MD&A section of 10-K filings classified as neutral in tone by the FinBERT-tone model (Huang *et al.*, 2023). Columns (1) and (2) present results for FLS sentences identified using the Li (2010) keyword approach and the Huang *et al.* (2023) FinBERT-FLS classifier, respectively. Columns (3) and (4) decompose the Huang *et al.* measure into specific FLS sentences (containing concrete, quantifiable forward-looking content) and non-specific FLS sentences (containing qualitative or general forward-looking content). All regressions include the full set of firm-level and macroeconomic controls reported in Table 2 (coefficients suppressed for brevity) and firm fixed effects. t-statistics are reported in brackets. Standard errors are clustered at the firm level. Variable definitions are provided in Appendix A. Continuous variables are winsorized at the 1st and 99th percentiles. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Frequency of Management Guidance, Horizon of Management Guidance, and Economic Policy Uncertainty (EPU)

VARIABLES	(1) Freq Guidance	(2) Horizon Guidance
LN(EPU)	-1.075*** [-12.625]	-11.260** [-2.559]
<u>Firm Controls</u>		
Ln(MVE)	0.360*** [8.130]	16.300*** [7.034]
BTM	0.230*** [2.902]	11.850*** [2.854]
Leverage	0.091 [0.454]	22.590** [1.965]
RetVol	-25.106*** [-8.296]	-657.784*** [-4.243]
Beta	0.328*** [5.583]	8.510** [2.446]
MeanTurn	27.276*** [5.152]	948.375*** [3.831]
Big4	0.467*** [3.870]	19.600*** [2.627]
Change_EARN	-0.050 [-0.302]	-32.400*** [-2.908]
Loss	-0.202*** [-3.090]	20.426*** [4.996]
EarnVol	-0.280 [-1.023]	-10.567 [-0.731]
<u>Economic Controls</u>		
Recession	-0.124* [-1.717]	4.491 [1.094]
Presidential_election	-0.197*** [-5.456]	-1.185 [-0.536]
Real GDP Growth	-0.211*** [-13.244]	-5.162*** [-6.326]
StockSentiment	-0.376*** [-12.306]	-6.528*** [-3.352]
JLN_MacroUncertainty	-0.379 [-0.699]	-30.819 [-1.079]
GDPDispersion	0.521*** [5.430]	4.315 [0.752]
Observations	13,850	13,850
R-squared	0.457	0.327
Firm FE	Yes	Yes
Cluster	Firm	Firm

This table presents results from firm the regressions of management forecast disclosures on Economic Policy Uncertainty (EPU). Column

(1) estimates an OLS regression model for *Freq_Guidance*, the number of annual EPS management forecasts issued by the firm in the fiscal year following Call *et al* (2017). Column (2) estimates an OLS regression model for *Horizon_Guidance*, the number of days between the firm's first annual EPS management forecast for the fiscal year and the fiscal year-end date. Management forecast data are obtained from LSEG IBES Management Guidance and restricted to annual EPS forecasts. $LN(EPU)$ is the natural logarithm of the firm-year average of the Baker, Bloom, and Davis (2016) news-based Economic Policy Uncertainty index over the 12 months ending on the firm's fiscal year-end. Firm-level controls follow Call *et al* (2017). All regressions include firm fixed effects. t-statistics are reported in brackets. Standard errors are clustered at the firm level. Variable definitions are provided in Appendix A. Continuous variables are winsorized at the 1st and 99th percentiles. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Voluntary Disclosure and Crisis Periods**Panel A: Event Study - DotCom Crisis (1998 – 2003)**

VARIABLES	(1) FL_Modify (Li)	(2) FL_Modify (Huang <i>et al</i>)	(3) Ln(CountFL S) (Li)	(4) Ln(CountF LS) (Huang <i>et al</i>)	(5) Ln(CountSpecific FLS) (Huang <i>et al</i>)	(6) Ln(CountNon- SpecificFLS) (Huang <i>et al</i>)
DotCom	0.010 [1.302]	0.018** [2.264]	0.236*** [7.167]	0.264*** [7.649]	0.111*** [3.638]	0.363*** [10.531]
Observations	13,015	13,015	13,966	13,966	13,966	13,966
R-squared	0.502	0.514	0.691	0.690	0.641	0.712
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm	Firm	Firm
Sample Window	1998-2003	1998-2003	1998-2003	1998-2003	1998-2003	1998-2003

This table presents results from the regressions of forward-looking statement (FLS) measures on a binary indicator for the DotCom crisis period. The sample is restricted to firm-years with fiscal years between 1998 and 2003, comprising three pre-crisis years (1998–2000) and three crisis years (2001–2003). The *DotCom* indicator equals one for fiscal years 2001 through 2003 and zero for fiscal years 1998 through 2000. Columns (1) and (2) estimate OLS regression models for the length-adjusted *FL_Modify* measure using FLS identified by the Li (2010) keyword approach and the Huang *et al.* (2023) FinBERT-FLS classifier, respectively. Columns (3) and (4) estimate OLS regression models for the log of the total number of FLS sentences in the MD&A identified by the Li (2010) approach and the Huang *et al.* (2023) classifier. Columns (5) and (6) decompose the Huang *et al.* count into the log of specific FLS sentences (containing concrete, quantifiable forward-looking content) and the log of non-specific FLS sentences (containing qualitative or general forward-looking content). All regressions include the full set of firm-level controls and macroeconomic controls reported in Table 2 (coefficients suppressed for brevity), excluding the NBER recession indicator and the presidential election year indicator to avoid mechanical overlap with the crisis dummy. All regressions include firm fixed effects. t-statistics are reported in brackets. Standard errors are clustered at the firm level. Variable definitions are provided in Appendix A. Continuous variables are winsorized at the 1st and 99th percentiles. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel B: Event Study – Financial Crisis (2005 - 2010)

VARIABLES	(1) FL_Modif y (Li)	(2) FL_Modify (Huang <i>et al</i>)	(3) Ln(CountFL S) (Li)	(4) Ln(CountF LS) (Huang <i>et al</i>)	(5) Ln(CountSpecific FLS) (Huang <i>et al</i>)	(6) Ln(CountNon- SpecificFLS) (Huang <i>et al</i>)
Financial Crisis	-0.022*** [-3.860]	-0.019*** [-3.299]	0.071*** [0.833]	0.066*** [0.401]	-0.006 [-0.823]	0.093*** [1.175]
Observations	12,853	12,853	13,563	13,563	13,563	13,563
R-squared	0.504	0.529	0.696	0.689	0.717	0.685
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

Cluster	Firm	Firm	Firm	Firm	Firm	Firm
Sample Window	2005-2010	2005-2010	2005-2010	2005-2010	2005-2010	2005-2010
This table presents results from firm fixed effects regressions of forward-looking statement (FLS) measures on a binary indicator for the Global Financial Crisis period. The sample is restricted to firm-years with fiscal years between 2005 and 2010, comprising three pre-crisis years (2005–2007) and three crisis years (2008–2010). The <i>Financial_Crisis</i> indicator equals one for fiscal years 2008 through 2010 and zero for fiscal years 2005 through 2007. Columns (1) and (2) estimate OLS regression models for the length-adjusted <i>FL_Modify</i> measure using FLS identified by the Li (2010) keyword approach and the Huang <i>et al.</i> (2023) FinBERT-FLS classifier, respectively. Columns (3) and (4) estimate OLS regression models for the log of the total number of FLS sentences in the MD&A identified by the Li (2010) approach and the Huang <i>et al.</i> (2023) classifier. Columns (5) and (6) decompose the Huang <i>et al.</i> count into the log of specific FLS sentences (containing concrete, quantifiable forward-looking content) and the log of non-specific FLS sentences (containing qualitative or general forward-looking content). All regressions include the full set of firm-level controls and macroeconomic controls reported in Table 2 (coefficients suppressed for brevity), excluding the NBER recession indicator and the presidential election year indicator to avoid mechanical overlap with the crisis dummy. All regressions include firm fixed effects. t-statistics are reported in brackets. Standard errors are clustered at the firm level. Variable definitions are provided in Appendix A. Continuous variables are winsorized at the 1st and 99th percentiles. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.						

Panel C: Event Study – Covid Crisis (2017 - 2022)

VARIABLES	(1) FL_Modify (Li)	(2) FL_Modify (Huang <i>et al.</i>)	(3) Ln(CountFL S) (Li)	(4) Ln(CountF LS) (Huang <i>et al.</i>)	(5) Ln(CountSpecific FLS) (Huang <i>et al.</i>)	(6) Ln(CountNon- SpecificFLS) (Huang <i>et al.</i>)
COVID	0.004 [0.381]	0.006 [0.544]	0.200*** [4.834]	0.197*** [4.547]	0.186*** [4.115]	0.191*** [4.421]
Observations	13,084	13,084	13,398	13,398	13,398	13,398
R-squared	0.501	0.519	0.721	0.716	0.745	0.707
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm	Firm	Firm
Sample Window	2017-2022	2017-2022	2017-2022	2017-2022	2017-2022	2017-2022

This table presents results from the regressions of forward-looking statement (FLS) measures on a binary indicator for the COVID-19 pandemic period. The sample is restricted to firm-years with fiscal years between 2017 and 2022, comprising three pre-crisis years (2017–2019) and three crisis years (2020–2022). The *COVID* indicator equals one for fiscal years 2020 through 2022 and zero for fiscal years 2017 through 2019. Columns (1) and (2) estimate OLS regression models for the length-adjusted *FL_Modify* measure using FLS identified by the Li (2010) keyword approach and the Huang *et al.* (2023) FinBERT-FLS classifier, respectively. Columns (3) and (4) estimate OLS regression models for the log of the total number of FLS sentences in the MD&A identified by the Li (2010) approach and the Huang *et al.* (2023) classifier. Columns (5) and (6) decompose the Huang *et al.* count into the log of specific FLS sentences (containing concrete, quantifiable forward-looking content) and the log of non-specific FLS sentences (containing qualitative or general forward-looking content). All regressions include the full set of firm-level controls and macroeconomic controls reported in Table 2 (coefficients suppressed for brevity), excluding the NBER recession indicator and the presidential election year indicator to avoid mechanical overlap with the crisis dummy. All regressions include firm fixed effects. t-statistics are reported in brackets. Standard errors are clustered at the firm level. Variable definitions are provided in Appendix A. Continuous variables are winsorized at the 1st and 99th percentiles. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 7: MD&A Tone (Loughran-McDonald Dictionary Measures) and Economic Policy Uncertainty (EPU)

VARIABLES	(1) Ln(LM Negative)	(2) Ln(LM Positive)	(3) Ln(LM Uncertainty)	(4) Ln(LM Complexity)
LN(EPU)	0.143*** [16.343]	-0.030*** [-3.600]	0.115*** [13.042]	0.085*** [7.405]
Ln(MDA_Length)	0.962*** [199.416]	0.919*** [203.091]	0.842*** [161.891]	0.808*** [143.195]
Observations	68,577	68,577	68,577	68,577
R-squared	0.917	0.923	0.908	0.857
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm

This table presents the results of regressions of Loughran and McDonald's (2011) dictionary word counts on Economic Policy Uncertainty (EPU). Columns (1) through (4) estimate OLS regression models for the log of the count of negative, positive, uncertainty, and complexity words in the MD&A section of 10-K filings, respectively, as classified by the Loughran and McDonald (2011) finance-specific word lists. LN(EPU) is the natural logarithm of the firm-year average of the Baker, Bloom, and Davis (2016) news-based Economic Policy Uncertainty index over the 12 months ending on the firm's fiscal year-end. Ln(MDA_Length), the natural logarithm of MD&A word count, is included as an additional control to ensure that the coefficients capture compositional shifts in language rather than mechanical increases in word counts due to longer filings. All regressions include the full set of firm-level and macroeconomic controls reported in Table 2, as well as firm fixed effects. t-statistics are reported in brackets. Standard errors are clustered at the firm level. Variable definitions are provided in Appendix A. Continuous variables are winsorized at the 1st and 99th percentiles. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

APPENDICES

Appendix A: Variable Definitions

Variable	Description
<i>Dependent Variables: Forward-Looking Statement (FLS) Modification</i>	
FL_Modify (Raw) (Li)	Raw year-over-year modification score of forward-looking statements in the 10-K MD&A section, following Li (2010). Computed as one minus the cosine similarity between TF-IDF vectors (stemmed tokens, L2-normalized) of the forward-looking sentences identified by the Li (2010) rule-based detector in the firm's year t MD&A versus year $t-1$ MD&A. Higher values indicate greater modification from the prior year. Computed only for consecutive firm-years.
FL_Modify (Raw) (Huang <i>et al</i>)	Raw year-over-year modification score of forward-looking statements identified following the Huang <i>et al.</i> (FinBERT-FLS) classification. Computed as one minus the cosine similarity between TF-IDF vectors of FLS sentences (both specific and non-specific FLS) identified by the FinBERT-FLS classifier in the firm's year t MD&A versus year $t-1$ MD&A. Computed only for consecutive firm-years.
FL_Modify (Li)	FL_Modify Raw (Li) adjusted for MD&A length. Computed as the residual from a regression of FL_Modify(Li) on a fifth-degree polynomial of MD&A word count, following the Brown and Tucker (2011) and Thomas <i>et al</i> (2023) length adjustment approach to remove the mechanical relationship between document length and modification scores.
FL_Modify (Huang <i>et al</i>)	FL_Modify Raw (Huang <i>et al</i>) adjusted for MD&A length using the same fifth-degree polynomial residualization on MD&A word count.
Ln(CountFLS)(Li)	Log of the total number of forward-looking sentences in the MD&A section, identified using the Li (2010) rule-based detector. A sentence is classified as

	forward-looking if it contains future-oriented verbs (will, should, can, could, may, might, expect, anticipate, etc.) and does not match exclusion criteria.
Ln(CountFLS)(Huang <i>et al</i>)	Log of the total number of forward-looking sentences in the MD&A section identified by the FinBERT-FLS classifier (Huang <i>et al.</i>). Computed as the sum of specific and non-specific FLS sentences.
Ln(CountSpecificFLS)(Huang <i>et al</i>)	Log of the number of specific forward-looking sentences in the MD&A as classified by FinBERT-FLS. Specific FLS provides quantifiable or concrete forward-looking information.
Ln(CountNon-SpecificFLS)(Huang <i>et al</i>)	Log of the number of non-specific forward-looking sentences in the MD&A as classified by FinBERT-FLS. Non-specific FLS provide qualitative or general forward-looking statements without concrete figures.
<i>Dependent Variables: FLS Tone</i>	
Tone FLS (Li)	Tone of forward-looking sentences identified by the Li (2010) rule. Computed as (positive sentence count – negative sentence count) / total FLS sentence count, where the sentiment of each FLS sentence is classified by FinBERT-tone of Huang <i>et al</i> (2023).
Tone FLS (Huang <i>et al</i>)	Tone across all FLS sentences (specific and non-specific) identified by FinBERT-FLS. Computed as (positive – negative) / total FLS, with sentiment classified by FinBERT-tone of Huang <i>et al</i> (2023).
Tone Specific FLS (Huang <i>et al</i>)	Tone restricted to specific FLS sentences, computed as (positive – negative) / total specific FLS.
Tone Non-Specific FLS (Huang <i>et al</i>)	Tone restricted to non-specific FLS sentences, computed as (positive – negative) / total non-specific FLS.
<i>Dependent Variables: Positive, Negative, and Neutral FLS Counts</i>	

Ln(PositiveCount) FLS (Li)		Log of the number of FLS sentences (Li detector) classified as positive in tone by FinBERT-tone.
Ln(PositiveCount) (Huang <i>et al</i>)	FLS	Log of the number of FLS sentences (FinBERT-FLS classification) classified as positive in tone by FinBERT-tone.
Ln(PositiveCount) FLS (Huang <i>et al</i>)	Specific	Log of the number of specific FLS sentences classified as positive in tone.
Ln(PositiveCount) Specific FLS (Huang <i>et al</i>)	Non-	Log of the number of non-specific FLS sentences classified as positive in tone.
Ln(NegativeCount FLS) (Li)		Log of the number of FLS sentences (Li detector) classified as negative in tone by FinBERT-tone.
Ln(NegativeCount (Huang <i>et al</i>)	FLS)	Log of the number of FLS sentences (FinBERT-FLS classification) classified as negative in tone by FinBERT-tone.
Ln(NegativeCount FLS (Huang <i>et al</i>)	Specific)	Log of the number of specific FLS sentences classified as negative in tone.
Ln(NegativeCount Non-Specific FLS) (Huang <i>et al</i>)	Non-	Log of the number of non-specific FLS sentences classified as negative in tone.
Ln(NeutralCount FLS) (Li)		Log of the number of FLS sentences (Li detector) classified as neutral in tone by FinBERT-tone.
Ln(NeutralCount FLS) (Huang <i>et al</i>)		Log of the number of FLS sentences (FinBERT-FLS classification) classified as neutral in tone by FinBERT-tone.
Ln(NeutralCount FLS) (Huang <i>et al</i>)	Specific	Log of the number of specific FLS sentences classified as neutral in tone.
Ln(NeutralCount Non-Specific FLS) (Huang <i>et al</i>)		Log of the number of non-specific FLS sentences classified as neutral in tone.
<i>Dependent Variables: Loughran and McDonald word counts</i>		

Ln(LM Negative)	Log of the count of words in the MD&A section classified as negative by the Loughran and McDonald (2011) finance-specific word list. The LM negative list contains 2,337 words that typically carry negative connotations in financial contexts
Ln(LM Positive)	Log of the count of words in the MD&A section classified as positive by the Loughran and McDonald (2011) finance-specific word list. The LM positive list contains words that carry positive connotations in financial contexts
Ln(LM Uncertainty)	Log of the count of words in the MD&A section classified as uncertainty-related by the Loughran and McDonald (2011) finance-specific word list. The LM uncertainty list contains words that convey ambiguity or unpredictability in financial contexts
Ln(LM Complexity)	Log of the count of words in the MD&A section classified as complex or litigious by the Loughran and McDonald (2011) finance-specific word list.
<i>Independent Variables: Uncertainty Measures</i>	
LN(EPU)	Natural logarithm of the firm-year average of the monthly news-based Economic Policy Uncertainty index (Baker, Bloom, and Davis 2016), computed as the mean of monthly EPU values over the 12 months ending on the firm's fiscal year-end reporting date. Source: policyuncertainty.com (Baker, Bloom, and Davis).
<i>Firm-Level FLS Controls (Following Li 2010 and Related Literature)</i>	
AbsChgStockLiquidity	Absolute value of the year-over-year change in firm-level stock liquidity. Stock liquidity is computed from CRSP daily data over the fiscal year.
AbsChgEPS	Absolute value of the year-over-year change in earnings per share (epsfx) scaled by the firm's fiscal year-end stock price (prcc_f) based on COMPUSTAT data.

AbsChgCurrentRatio	Absolute value of the year-over-year change in the firm's current ratio (act/lct), based on COMPUSTAT data.
AbsChgDebtDue	Absolute value of the year-over-year change in debt in current liabilities (ddl) scaled by total assets (at), based on COMPUSTAT data.
AbsChgLeverage	Absolute value of the year-over-year change in total liabilities (lt) scaled by total assets (at), based on COMPUSTAT data.
AbsChgFCF	Absolute value of the year-over-year change in free cash flow (oancf – capx) scaled by total assets (at), based on COMPUSTAT data.
AbsChgStdReturn	Absolute value of the year-over-year change in the standard deviation of daily stock returns, based on CRSP data.
Downsize	Indicator equal to 1 if the firm experienced a decrease in total assets (at) of one-third or more from the prior year, and 0 otherwise. Source: Compustat Fundamentals Annual.
Acquire	Indicator equal to 1 if the firm experienced an increase in total assets (at) of one-third or more from the prior year (proxy for a major acquisition), and 0 otherwise, based on COMPUSTAT data.
Size	Natural logarithm of total assets (at), based on COMPUSTAT data.
Big6	Indicator equal to 1 if the firm's auditor (au) is one of the Big 6 auditors (au codes 1 through 9), and 0 otherwise, based on COMPUSTAT data.
Num8kfilings	Number of 8-K filings submitted by the firm to the SEC in the 365 days ending on the firm's fiscal year-end date. 8-K amendments are excluded.
Litigation	Indicator equal to 1 if the firm operates in a high-litigation-risk industry, defined as SIC codes in the ranges 2833-2836, 8731-8734, 3570-3577, 7370-

	7374, 3600-3674, and 5200-5961, and 0 otherwise. Source: Compustat (SIC); industry classification following Francis, Philbrick, and Schipper (1994).
HHI	Herfindafl-Hirschman Index of industry concentration at the 2-digit SIC level, computed as the sum of squared revenue (revt) shares of all Compustat firms within each fiscal year and 2-digit SIC industry.
<i>Other Variables</i>	
OANCF	Operating cash flow (oancf) scaled by total assets (at), based on COMPUSTAT data.
LeverageRatio	Total debt (dt) divided by common equity (ceq), based on COMPUSTAT data.
CurrentRatio	Current assets (act) divided by current liabilities (lct), based on COMPUSTAT data.
Ln(MDA_Length)	Natural logarithm of MD&A word count, used in robustness regressions of raw FL_Modify scores to control for document length.
<i>Macroeconomic Controls</i>	
Recession	Indicator equal to 1 if any month within the 12-month window ending on the firm's fiscal year-end date is classified as an NBER recession month, and 0 otherwise. Source: NBER recession indicator (USREC) via FRED.
Presidential_election	Indicator equal to 1 if the fiscal year is a U.S. presidential election year (1996, 2000, 2004, 2008, 2012, 2016, 2020), and 0 otherwise.
Real GDP Growth	Firm-year average of monthly real GDP growth over the 12 months ending on the firm's fiscal year-end reporting date. Source: FRED.

StockSentiment	Firm-year average of the Baker and Wurgler (2006) investor sentiment index over the 12 months ending on the firm's fiscal year-end reporting date. Source: Jeffrey Wurgler's investor sentiment data.
JLN_MacroUncertainty	Firm-year average of the Jurado, Ludvigson, and Ng (2015) one-year-ahead macroeconomic uncertainty index over the 12 months ending on the firm's fiscal year-end reporting date. Captures the conditional volatility of the unpredictable component of a broad set of macroeconomic and financial time series. Source: Sydney Ludvigson's macro uncertainty data (FRED series JLNUM12M).
GDPDispersion	Forecaster disagreement about real GDP growth, measured as the dispersion (second-quartile range) of one-year-ahead real GDP forecasts from the Livingston Survey. Merged as-of fiscal year-end. Source: Federal Reserve Bank of Philadelphia, Livingston Survey.
<i>Management Forecast Controls</i>	
Freq_Guidance	Number of EPS management forecasts issued by the firm for the fiscal year, counted from LSEG IBES Management Guidance (annual periodicity, EPS measure). Source: LSEG IBES Guidance.
Horizon_Guidance	Number of days between the date of the firm's first EPS management forecast for the fiscal year and the fiscal year-end date. Source: LSEG IBES Guidance.
Ln(MVE)	Natural logarithm of market value of equity, computed as fiscal year-end stock price (prcc_f) times common shares outstanding (csho), based on COMPUSTAT data.
BTM	Book-to-market ratio, computed as stockholders' equity (seq) divided by market value of equity (prcc_f $\times$ csho), based on COMPUSTAT data.

Leverage	Total long-term debt plus debt in current liabilities $((dltt + dd1) / at)$, based on COMPUSTAT data.
RetVol	Standard deviation of daily stock returns over a 252-trading-day rolling window. Source: CRSP daily stock file.
Beta	Market beta, estimated as the rolling 252-trading-day covariance of daily firm returns with the CRSP value-weighted index return, divided by the variance of the index return. Source: CRSP daily stock file.
MeanTurn	Mean share turnover, computed as the 252-day rolling average of daily trading volume divided by common shares outstanding (csho). Source: CRSP daily stock file; Compustat Fundamentals Annual.
Big4	Indicator equal to 1 if the firm is audited by a Big 4 auditor (au codes 4 through 7) and 0 otherwise. Set to missing if au is 0. Source: Compustat Fundamentals Annual.
Change_EARN	Change in earnings, computed as $(ib_t - ib_{\{t-1\}}) / at_{\{t-1\}}$, where ib is income before extraordinary items and at is total assets, based on COMPUSTAT data.
Loss	Indicator equal to 1 if income before extraordinary items (ib) is negative, and 0 otherwise, based on COMPUSTAT data.
EarnVol	Earnings volatility, computed as the rolling 5-year standard deviation of earnings (ib / at) , measured over years $t-5$ to $t-1$ (lagged), based on COMPUSTAT data.
<i>Crisis Period Indicators</i>	

Crisis Period	(DotCom, Financial, COVID)	Indicator equal to 1 if the fiscal year falls in any of the three crisis windows used in Table 5 (DotCom 2001-2003, Financial Crisis 2008-2010, COVID 2020-2022), and 0 otherwise.
DotCom (2001-2003)		Indicator equal to 1 if the fiscal year is 2001, 2002, or 2003, and 0 otherwise.
Financial Crisis (2008-2010)		Indicator equal to 1 if the fiscal year is 2008, 2009, or 2010, and 0 otherwise.
COVID (2020-2022)		Indicator equal to 1 if the fiscal year is 2020, 2021, or 2022, and 0 otherwise.