

Looking under the Hood: Quantitative vs Qualitative Inputs to Analysts' Forecasts of Fundamental Risk

Khrystyna Bochkay* Peter Joos†

Abstract

We study how sell-side analysts map quantitative and qualitative information from quarterly earnings conference calls into subsequent forecasts of fundamental firm risk. In terms of quantitative information, we find that analysts' risk forecasts increase in the magnitude of the earnings surprise (of either sign) and in the presence of a forecast walk-down. In contrast, analysts' risk forecasts decrease when managers issue earnings guidance and provide more financially-oriented disclosures. In terms of qualitative information, we find that more optimistic earnings calls and calls with more analyst questions result in lower risk forecasts. We further document a stronger association between earnings call information and risk forecasts during periods of high macroeconomic uncertainty, resulting in better forecast calibration. Our results are robust to alternative empirical specifications and enhance our understanding of the analyst forecasting process.

Keywords: analysts' risk forecasts, quantitative and qualitative information, unexpected earnings, linguistic tone, macroeconomic uncertainty.

JEL Classifications: G01, G11, G20, G24.

*Khrystyna Bochkay (corresponding author): Miami Business School, University of Miami, Coral Gables, FL 33146. Email: kbochkay@bus.miami.edu. Phone: +1-305-284-2334.

†Peter Joos: INSEAD, Asia Campus, 1 Ayer Rajah Avenue, 138676 Singapore, Singapore. Email: peter.joos@insead.edu. Phone: +65-6799-5386.

We would like to thank Dan Amiram, Vasiliki Athanasakou, Dan Bens, Sanjeev Bhojraj, Indraneel Chakraborty, Roman Chychyla, Ed deHaan (discussant), John Hand, Gilles Hilary, Thomas Keusch, Dave Larcker, Charles Lee, Tim Loughran, Michelle Lowry, Xiumin Martin, Dhananjay Nanda, Sundaresh Ramnath, Cathy Schrand, and seminar participants at the INSEAD brownbag, the ABFER 2017 conference, the European Accounting Association Meeting 2018, Stanford Summer Camp 2018, London School of Economics, Tilburg University, UC Berkeley and the University of Connecticut for their helpful comments and suggestions.

1 Introduction

Analysts are preeminent information intermediaries in capital markets, making their research one of the most studied topics in the accounting and finance literature (Bradshaw, 2011). Traditionally, academic researchers examine properties and consequences of analysts' earnings and target price (single-point) forecasts as they provide information on expected payoffs of an investment. However, to evaluate the profitability of an investment, investors also require information about the riskiness of the payoffs, as higher risk investments generally earn higher returns. In other words, to obtain valuable insights from analyst research, investors need to understand potential risks of a firm not achieving analysts' expectations. Although the importance of analysts' risk forecasts is widely recognized by academics, regulators, and practitioners, the paucity of data has limited research in this area.¹ To address this gap, in this paper, we use a sample of investment reports with analysts' forecasts of fundamental risk to examine which firm-level information analysts consider when assessing risk. We also examine how analysts process information under conditions of increased macroeconomic uncertainty - a time when analyst research likely matters more and firms' past outcomes are less informative (Loh and Stulz, 2018).

Our focus on analysts' usage of information follows calls to open up the "black-box" of sell-side analysts' forecast activities (e.g., Ramnath et al. (2008), Bradshaw (2011), Brown et al. (2015), and Kothari et al. (2016)). While the literature on properties of analyst earnings forecasts (e.g., accuracy, bias) is abundant, there is little evidence on how analysts generate their risk forecasts, i.e., *what* information analysts use and *how* they use it. Relevant to our paper, a few prior studies on analyst risk forecasts (e.g., Lui et al. (2007, 2012) and Joos et al. (2016)) find that analysts' risk forecasts are associated with traditional measures of firm risk

¹For instance, Zmijewski (1993) issued an early call for research into analysts' ability to assess firm risk. Similarly, motivated by economic downturns of the early 2000s and subsequent strong investors' demand for risk-related information in analyst reports, Morgan Stanley augmented its forecasting platform in 2007 by requiring its analysts to forecast downside and upside risk in addition to providing the mean forecast (see Weyns et al. (2007)). In addition, in its Research Analyst Rules, FINRA requires analysts to accompany their forecasts and recommendations "by a clear explanation of any valuation method used and a fair presentation of the risks that may impede achievement of the recommendation, rating or price target" (FINRA (2014)).

such as beta, idiosyncratic volatility, book-to-market, etc. However, these measures of risk are generally extrapolations of the past and fail to account for specific business fundamentals and potential economic developments (Klarman, 1991; Weyns et al., 2007). In this paper, we therefore study whether different measures of information about firm fundamentals are relevant for risk forecasting, above and beyond traditional measures of risk.²

To study the specific role of information variables for analysts' risk forecasts, we construct a unique research setting by combining a sample of analyst investment reports with a comprehensive sample of earnings conference calls spanning the period of 2007 through 2012. We zoom in on reports published soon after quarterly earnings conference calls, resulting in a sample of 3,740 observations. Each observation comprises a report that contains an individual analyst's most likely valuation for the firm (i.e., base-case valuation or target price) and an expected distribution (or range) of scenario-based valuations (i.e., base case plus upside/downside valuations). We use the difference between a report's upside and downside valuation forecasts (i.e., range) to define a measure of analyst fundamental risk forecast.

We focus on earnings conference calls because, out of all sources of information, sell-side analysts consider earnings call events to be highly useful in determining their earnings forecasts (see survey evidence in Brown et al. (2015)). Moreover, earnings conference calls are not only a major form of communication firms use to supplement their regulatory filings, they also present market participants with information about the firm's performance and prospects in both quantitative and qualitative form (Matsumoto et al., 2011). To capture the richness of information in earnings calls, we use different quantitative and qualitative measures identified by prior literature.

Controlling for traditional measures of risk, time, industry and analyst fixed effects, we find that quantitative and qualitative information in earnings conference calls jointly matter for risk forecasting. Specifically, we find that earnings surprise (of either sign) and the presence of a forecast walk-down increase analyst risk forecasts, while earnings guidance

²Joos et al. (2016) find that analyst risk forecasts are unbiased (unlike target price or EPS forecasts), making them an ideal forecast metric to study the role of different information inputs to the forecasting process.

and more financially-oriented disclosures decrease risk forecasts. These results suggest that shocks to analysts' expectations exacerbate uncertainty in analyst forecasts, while additional financial disclosures mitigate this uncertainty. In terms of qualitative information, we find that earnings call tone and the number of analysts' questions in the call decrease analysts' risk forecasts. These results are consistent with analysts using qualitative information in earnings calls as an additional signal when forecasting firm risk.

We next examine if conditions of macroeconomic uncertainty affect analysts' reliance on quantitative and qualitative information when forecasting future risk. As argued by [Bloom \(2009\)](#) and [Loh and Stulz \(2018\)](#), macroeconomic uncertainty leads to greater variation in outcomes across firms and over time. Therefore, heightened macroeconomic uncertainty likely renders analysts' risk forecasts particularly salient for capital market participants. Indeed, recent studies by [Amiram et al. \(2017\)](#) and [Loh and Stulz \(2018\)](#), show that conditions of increased macroeconomic uncertainty increase investors' reliance on analyst advice, resulting in timelier and longer analyst reports. While findings in [Loh and Stulz \(2018\)](#) are consistent with analysts changing "what they do" during bad times, neither their study nor [Amiram et al. \(2017\)](#) examine how analysts change their forecasting model to respond to the increased demand for their research during bad times. To examine analysts' use of information during bad economic times, we create high macroeconomic uncertainty indicators based on the CBOE Volatility Index (VIX) and recession periods as identified by the National Bureau of Economic Research (NBER). We find that analysts generally do not change their reliance on quantitative information during bad times, while their reliance on qualitative information, such as earnings call optimism, dramatically increases. This result suggests that analysts recognize differences in usefulness of both types of information when macroeconomic uncertainty increases.

Having established analysts' reliance on quantitative and qualitative information in general and during periods of high macro uncertainty, we next examine whether this reliance results in better forecasts. We answer this question by studying the relation between analyst risk forecasts and *ex post* absolute valuation errors and stock return volatility, conditional

on the mapping of earnings call information into risk forecasts documented above. In other words, we examine the relation between our measures of quantitative and qualitative information and absolute valuation errors and return volatility, with the mediating role for analysts' risk forecasts. We find that higher valuation uncertainty as captured by analysts' risk forecasts results in higher absolute valuation errors. Similarly, higher risk forecasts predict increased return volatility in the year following the forecast. Further, all variables shown to be relevant for risks forecasts (i.e., earnings surprise, earnings guidance, forecast walk-down, financially-oriented disclosures, earnings call tone, and analysts' questions in the earnings call) also have indirect effects, mediated through analysts' risk forecasts, on analyst forecast accuracy and subsequent return volatility. That is, their inclusion in risk forecasts helps tighten the positive relation between risk forecasts and absolute valuation errors, and makes risk forecasts better predictors of future return volatility. When we take into account conditions of high macroeconomic uncertainty, we find that the calibration of risk forecasts improves, i.e., the relation between risk forecasts and valuation errors and future return volatility strengthens, and that both quantitative and qualitative information contributes to this improvement. Overall, these results are consistent with our earlier findings and point to analysts using different types of firm-level information and appropriately changing their risk forecasts during periods of high macroeconomic uncertainty.

We carry out several additional analyses and robustness tests to provide further support for our main findings. First, we examine cases where the earnings surprise and earnings call tone provide 'contradictory' signals, i.e., very high (low) earnings surprise is followed by a relatively pessimistic (optimistic) discussion in the earnings call. We find that earnings call tone is relevant for analyst risk forecasts only when it *contradicts* the quantitative surprise signal, but not when it confirms it. This result is consistent with analysts considering tone of earnings calls as a *credible* signal: when tone is at odds with the earnings surprise, it provides additional information about future risk. When tone simply confirms the earnings surprise, it seems to have limited value for risk forecasts. Second, we expand the evidence on the earnings surprise by considering the information roles of revenue vs. expense surprises. We

find that only the revenue-based surprise is relevant for analysts' risk forecasts. This result is consistent with analysts recognizing the greater persistence of revenue surprises as documented in [Ertimur et al. \(2003\)](#). Third, we verify the generalizability of our findings using target price forecasts available in IBES. Specifically, we replace our (explicit) risk forecast metric in analyst reports with target price range and dispersion metrics constructed using a broad set of IBES analysts. Consistent with our main results, we find that quantitative and qualitative information in earnings calls is relevant to the range and dispersion of target price forecasts. Finally, we carry out our analyses controlling for past risk forecasts, distinguishing between information in different parts of the earnings call, and considering positive and negative components of earnings call tone. The main takeaways from our earlier tests remain unchanged.

We contribute to the analyst literature by examining quantitative and qualitative inputs to analysts' risk forecasts. While risk assessment is an important ingredient of an investment decision, research on risk forecasting has been relatively scarce and has mainly focused on how traditional measures of risk (e.g., beta, volatility) relate to forecasts. To our knowledge, we are the first to show that earnings surprise (of either sign) and forecast walk-down increase analysts' perceptions of risk, while management earnings guidance, financially-relevant disclosures, earnings call optimism, and analysts' scrutiny of the earnings call reduce analysts' risk forecasts. As such, we contribute to the literature by showing that analysts consider different quantitative and qualitative measures in their analyses (e.g., [Asquith et al. \(2005\)](#), [Bradshaw et al. \(2017\)](#)). Our paper also relates in particular to [Mayew and Venkatachalam \(2012\)](#), who study investors' and analysts' reactions to vocal cues in earnings conference calls and find that, while investors value this qualitative information, analysts only *partially* incorporate it when changing their stock recommendations. They interpret this finding as being consistent with strategic analyst incentives. In contrast to [Mayew and Venkatachalam \(2012\)](#), who examine earnings forecasts and stock recommendations, we focus on analysts' risk forecasts. [Joos et al. \(2016\)](#) find that these risk forecasts do not exhibit strategic biases, which helps reconcile our results with those in [Mayew and Venkatachalam \(2012\)](#).

We also contribute to the literature on the role of macroeconomic uncertainty in capital markets. Several studies examine how macroeconomic uncertainty affects capital market participants’ usage of different types of information (e.g., [Johnson \(1999\)](#), [Garcia \(2013\)](#), [D’Aurizio et al. \(2015\)](#)). Recently, [Loh and Stulz \(2018\)](#) conclude that analysts’ role becomes more important during bad economic times and that analysts work harder to fulfill that role. We contribute to this stream of research by showing that analysts rely more on qualitative information in periods of increased macroeconomic uncertainty and that this increased reliance improves the calibration of their risk forecasts.

More generally, our findings enhance our understanding of how one important group of market participants, sell-side analysts, handles information arriving in different forms to forecast firm fundamentals under potentially changing market circumstances. As such, we contribute to research efforts to open up the “black-box” of sell-side analysts’ forecasting process, as suggested by [Ramnath et al. \(2008\)](#), [Bradshaw \(2011\)](#), [Brown et al. \(2015\)](#), and [Kothari et al. \(2016\)](#).

2 Background and Predictions

2.1 Motivation and Empirical Setting

Our study connects two broad research themes on the role of information in capital markets by examining the joint role of quantitative and qualitative information for decision making and by analyzing how conditions of macroeconomic uncertainty affect market participants’ use of information. In addressing these issues, we focus on information usage by one important group of capital market participants, namely sell-side analysts. Sell-side analysts are important intermediaries who help to bridge the information gap between companies and investors. Analysts accumulate, process, summarize, and publish value-relevant information, so that investors can make more informed and timely decisions. Consequently, numerous studies in the literature have examined properties of analysts’ single-point earnings forecasts and stock recommendations and their information value to the investment community. While understanding the consequences of analysts’ forecasts is important, recent studies encourage future research to focus more on how analysts generate their forecasts and recommendations.

For example, in a recent literature review on analysts’ forecasts, [Kothari et al. \(2016\)](#) emphasize that “understanding how analysts form and revise their expectations is crucial.” In a similar vein, [Ramnath et al. \(2008\)](#), [Bradshaw \(2011\)](#), and [Brown et al. \(2015\)](#) highlight the importance of opening the “black box” of analysts’ advice - *what* information analysts use and *how* they use it. In this paper, we attempt to address this call by examining the role of quantitative and qualitative information in the analyst forecasting process. While most prior studies focus almost exclusively on earnings forecasts and stock recommendations, we examine analysts’ risk forecasts.³

We base our measure of analysts’ risk forecasts on scenario-based valuation estimates provided by Morgan Stanley analysts in their investments reports. Starting in 2007, Morgan Stanley requires its analysts to expand their analyses to present both upside and downside valuation scenarios, called bull and bear cases, in addition to the base-case expectations for the company’s stock price, over the following 12 months (see [Weyns et al. \(2007\)](#) and [Srinivasan and Lane \(2011\)](#) for details).⁴ The base-case valuation is the most likely outcome expected by the analyst and is analogous to the traditional target price forecast. The bull and bear cases reflect analyst’s beliefs about firm value under alternative upside and downside scenarios, respectively.⁵ These scenarios could materialize if there are changes in a company’s operating environment, such as more or less demand for a critical product, new competition or regulations, or changes in the economy. We use the width of the valuation range or the difference between a report’s upside (bull) and downside (bear) valuation forecasts, scaled by the midpoint of the analysts’ valuation range, as our measure of analysts’ valuation risk forecast, denoted as *Spread*. Intuitively, the tighter (wider) *Spread* at the report date, the

³Evidence on analyst risk forecasts is scarce, despite a more pronounced recent attention to investor risk perceptions in the literature (e.g., [Kothari et al. \(2009\)](#); [Kravet and Muslu \(2013\)](#); [Hope et al. \(2016\)](#)).

⁴Figure A1 shows an example of scenario-based valuation estimates created under the risk-return framework at Morgan Stanley. [Joos et al. \(2016\)](#), [Joos and Piotroski \(2017\)](#) and [Hope et al. \(2016\)](#) are examples of recent papers that use Morgan Stanley’s reports.

⁵As discussed in [Weyns et al. \(2007\)](#), the risk-reward framework requires analysts to explore alternative future outcomes of fundamental value drivers as they construct their three scenarios. The framework however does not require analysts to provide an explicit confidence interval within which the stock price is expected to fall since the objective of the scenario-based approach is not to provide a continuous probability distribution of value (see also [Joos et al. \(2016\)](#)).

more certain (uncertain) the analyst is about the firm’s future value and payoffs.

We use earnings announcements accompanied by earnings conference calls as our source of firm-specific quantitative and qualitative information that could be relevant for analysts’ risk forecasts. Earnings conference calls are one of the major forms of firm disclosures. In contrast to the formal and even boilerplate language often seen in regulatory filings (e.g., annual and quarterly SEC reports), conference calls are more timely, they involve spoken language, and are arguably more informative. Moreover, analysts’ active participation in conference calls and increased number of subsequent forecast revisions suggests that analysts find these events relevant.⁶ Indeed, [Brown et al. \(2015\)](#) survey sell-side analysts to understand which information is the most useful for their forecasting activities. Earnings calls are listed as the third most relevant source after analysts’ own industry expertise and their private communications with management (see Table 1 in [Brown et al. \(2015\)](#)).

2.2 Quantitative and Qualitative Inputs to Analysts’ Risk Forecasts

Analysts can use various sources (both private and public) and their own research and expertise to generate risk forecasts for a given stock. While we cannot observe each analyst’s private information, we hypothesize that analysts will incorporate information from public sources such as corporate disclosures. Given our focus, we construct several measures of quantitative and qualitative information using different aspects of the earnings call setting.⁷ Below, we describe our variables of interest and summarize our predictions regarding the relationship between *Spread* and these quantitative and qualitative information measures.

⁶[Matsumoto et al. \(2011\)](#), [Mayew and Venkatachalam \(2012\)](#), [Chen et al. \(2014\)](#), [Huang et al. \(2017\)](#), and [Bochkay et al. \(2018\)](#) are examples of recent studies that focus on the information value of earnings conference calls to the market.

⁷Earnings announcements and earnings conference calls are joint events, which typically occur within a day from each other (in our sample, 85.72% (13.96%) of conference calls occur on the day of (after) the earnings announcement). Even though the discussion at the beginning of the call is typically a recap of a company’s press release, the questions-and-answers (Q&A) section of the call brings new insights as it is driven by analysts’ questions. In addition, many earnings conference calls involve explicit financial forecasts as well as verbal forward-looking statements describing expected performance. As such, our metrics of quantitative and qualitative information are intended to capture information in both earnings press releases and conference calls.

Throughout our discussion, our maintained null hypothesis is that analysts’ risk forecasts do not incorporate information from earnings conference calls.

1. *Quantitative Information in Earnings Conference Calls*

(a) *Earnings Surprise*

Earnings that deviate strongly from expectations could be indicative of the uncertainty in the forecasting environment (Matsumoto, 2002). We measure earnings surprise relative to the analyst consensus, UE , to capture this uncertainty. We predict that greater shocks to analysts’ expectations result in higher risk forecasts. In our research design, we distinguish between negative and positive earnings surprises. Generally, managers try avoiding negative earnings surprises because “bad news” lead to negative market reactions and bad reputation (Matsumoto, 2002; Bartov et al., 2002; Skinner and Sloan, 2002). In addition, many analysts facilitate managers’ ability to meet or beat analysts’ expectations by reducing their forecasts (Cotter et al., 2006).⁸ As such, to estimate the differential effect of good vs. bad news on analysts’ risk perceptions, we include $GoodNews$, equal to UE if UE is positive and 0 otherwise, and $BadNews$, equal to $|UE|$ if UE is negative and 0 otherwise. We also include an indicator variable for bad news, $BadNewsInd$, to estimate the difference in risk perceptions based solely on sign (i.e., regardless of the surprise magnitude).⁹

(b) *Management Guidance*

Management earnings guidance reduces the information asymmetry between managers and investors, leading to less uncertainty about future performance (Diamond and Verrecchia, 1991; Baginski et al., 1993; Clement et al., 2003). As a result, we predict a negative relation between $Guidance$ and analysts’ risk perceptions. In addition, if management earnings guidance is lower than the existing analyst consensus, analysts’ perceptions of future risks potentially increase. We include an indicator variable $GuidanceLow$ to capture observations

⁸Controlling for the sign of unexpected earnings is important since Barron et al. (2008) show that analysts react differently to good vs. bad earnings surprises. In particular, they find that large or negative earnings surprises motivate analysts to put more effort into developing future forecasts. In addition, investors react differently to good vs. bad news during times of high macroeconomic uncertainty (Williams, 2015).

⁹In econometrics, the method of estimating two separate slopes for a variable is known as *interrupted* regressions (see Marsh and Cormier (2001); Simonsohn (2018)). This method is often used to model non-linear relationships between variables.

with management guidance lower than the analyst consensus.

(c) *Prevalence of Financially-Oriented Information*

Matsumoto et al. (2011) measure the extent to which narrative disclosures in earnings conference calls are financially oriented and find that managers provide more (less) of these disclosures when performance is good (bad). Therefore, to the extent that financially oriented disclosures in earnings calls vary with performance, they could also affect analysts' risk forecasts. Accordingly, we predict that the prevalence of financial terms in earnings calls, *FinTerms*, is associated with lower risk forecasts.

(d) *Earnings-Related Forward-Looking Statements*

In addition to providing an explicit management forecast of future earnings (i.e., *Guidance*), many companies issue forward-looking statements discussing future earnings. If analysts find such narrative disclosures relevant to reduce uncertainty around a firm's future, we expect a negative relation between analysts' risk forecasts and the amount of earnings-related forward-looking statements. We use the methodology in Bozanic et al. (2018) to identify earnings-related forward-looking statements in conference calls, *FLS Earnings*.

(e) *Forecast Walk-down*

There is well-documented evidence in the literature that analysts' forecasts decline as the end of the period approaches. Studies characterize this pattern of earnings forecasts as the forecast walk-down (e.g., Matsumoto (2002); Richardson et al. (2004); Cotter et al. (2006)) and generally attribute it to analysts' optimistic biases and self-serving incentives. Since we measure *UE* using recent analyst consensus as a benchmark, this could imply that our surprise metrics do not fully capture the change in earnings expectations during the quarter prior to the earnings announcement. To address this empirical issue, we define an indicator variable *Walkdown*, equal to one if there is a forecast walk-down in the quarter preceding the earnings announcement and zero otherwise, and include it as an additional metric of quantitative information. Since there could be different reasons for a walk-down (e.g., management feedback, strategic behavior by analysts), we do not formulate a signed prediction on this variable. We simply expect that, if there is information value in the

presence of a walk-down, *Walkdown* will be associated with analysts' risk forecasts.

2. *Qualitative Information in Earnings Conference Calls*

(a) *Earnings Call Tone*

Recent theoretical arguments and empirical evidence suggest that favorable (unfavorable) disclosures are associated with lower (higher) firm risk as captured by the firm's cost of capital and return volatility. For instance, [Ng et al. \(2009\)](#) show (both theoretically and empirically) that firm performance reports help build expectations about future value and uncertainty. They find that the assessment of risk increases as firm performance declines, suggesting a directional link between performance measures and the firm's risk. [Kothari et al. \(2009\)](#) extend [Ng et al. \(2009\)](#)'s work by providing a large sample empirical evidence on the directional relation between disclosure tone (optimistic/pessimistic) and the firm's capital market environment as measured by the cost of capital, return volatility, and analyst dispersion. Recent work by [Campbell et al. \(2014\)](#) and [Campbell et al. \(2017\)](#) adopts the same framework and finds similar evidence of a directional link between the tone of the firm's SEC filings and investors' assessments of risk. In our setting of analysts revising their forecasts of future stock realizations following earnings calls, we accordingly predict that more positive (negative) conference call tone, *Tone*, will be associated with lower (higher) analysts' risk forecasts.

(b) *Conference Call Uncertainty*

We complement our directional *Tone* metric with a measure that captures the extent of uncertainty or imprecision in earnings call disclosures. To the extent that more uncertain or imprecise disclosures make it more difficult for analysts to gauge firms' future prospects, we predict that when firms use more uncertain language in earnings calls, analysts' risk perceptions increase. We use [Loughran and McDonald \(2011\)](#)'s uncertainty word list to capture the extent of uncertainty in earnings calls, *Uncertainty*.

(c) *Non-Earnings-related Forward-looking Statements*

In addition to earnings-related forward-looking statements, [Bozanic et al. \(2018\)](#) also identify non-earnings related forward-looking statements in management disclosures, or *FLS Other*.

Their analysis shows that firms provide more non-earnings related forward-looking information when uncertainty is high. In our setting, if non-earnings related forward-looking information in earnings calls helps analysts to assess future risk, we predict a negative association between *FLS Other* and analysts' risk forecasts.

(d) *Analysts' Questions*

Earnings conference calls provide analysts and investors with a unique opportunity to question management about the realized as well as expected company performance. According to the survey evidence in [Brown et al. \(2015\)](#), analysts consider the questions-and-answers (Q&A) section of earnings conference calls as the second most informative source of management communications, after private communications with management being the first. Relatedly, [Hollander et al. \(2010\)](#) point out that limited discussion during a conference call potentially indicates that the firm is withholding bad news. As such, we predict that the number of questions asked in earnings conference calls, or *AnalystQs*, helps reduce analysts' perception of future firm risk as analysts acquire more information.

2.3 Macroeconomic Uncertainty and Analysts' Reliance on Quantitative and Qualitative Information in Earnings Calls

Our predictions in Section 2.2 are intended to understand the joint role of quantitative and qualitative information in earnings conference calls for analysts' risk forecasts. However, quantitative and qualitative information as well as analysts' use of information potentially differ depending on the general macroeconomic uncertainty. In this section, we augment our analysis by considering how conditions of macroeconomic uncertainty affect analysts' use of quantitative and qualitative information to generate risk forecasts.

The financial crisis of 2008 prompted a lot of attention to the investors' and analysts' behavior during periods of increased uncertainty. For example, [Loh and Stulz \(2018\)](#) find that during bad times investors react more strongly to analysts' forecasts and that analysts' work harder by issuing more frequent and longer reports and generating more accurate

forecasts.¹⁰ Relatedly, [Joos et al. \(2016\)](#) show that following the financial crisis of 2008 analysts not only changed the relative magnitude of their risk forecasts, but also strengthened the relation of their forecasts with known risk metrics. While this recent research highlights the importance of macroeconomic uncertainty for analysts' effort and forecasts, it does not answer the question of whether the state of the economy affects the way in which analysts use firm-level information to generate their forecasts.

Since our focus is on the role of quantitative and qualitative information for analysts' risk forecasts, it is important to understand which type of information is more informative when the macroeconomic uncertainty increases. Previous studies provide some evidence on changes in *investors'* reliance on different types of information during periods of increased macroeconomic uncertainty. For instance, [Johnson \(1999\)](#) finds that earnings persistence and earnings response coefficients (i.e., the magnitude of the stock price response to earnings news) are lower during recessions. This finding is consistent with quantitative information being less informative to investors during periods of high macroeconomic uncertainty. In a different setting, [D'Aurizio et al. \(2015\)](#) makes a similar observation that during the global crisis of 2008, banks reduced their reliance on quantitative information in the bank lending process as this information became less reliable. With respect to qualitative information, a recent study by [Garcia \(2013\)](#) finds that investors' response to media sentiment (as captured by the tone of financial columns in the *New York Times*) is higher during recessions.

Given this evidence on investors' reactions to information as a function of different macroeconomic conditions, there appear to be good reasons to believe that analysts' reliance on quantitative vs. qualitative information will be different depending on the level of macroeconomic uncertainty. However, *a priori* it is not clear in which directions the weights on different types of information will tilt as macro uncertainty increases. On one hand, quantitative financial information could be more informative, relative to qualitative information, during times of increased macroeconomic uncertainty as it is more precise, verifiable, and structured. On the other hand, high macro uncertainty may lead to greater variation

¹⁰[Arand and Kerl \(2012\)](#) and [Amiram et al. \(2017\)](#) are related studies examining analysts' forecasting behavior during bad times.

in quantitative outcomes across firms and over time (Bloom, 2009; Loh and Stulz, 2018). Moreover, quantitative information is often backward-looking (e.g., earnings for the period just ended), lacking the ability to predict future performance when uncertainty increases.¹¹

At the same time, given the unstructured and (often) unregulated nature of qualitative information, managers potentially can use qualitative disclosures to provide a more informative outlook on their companies' performance and prospects during uncertain times. In this vein, Tetlock et al. (2008) find evidence consistent with qualitative information having its strongest predictive power for earnings and returns when it captures hard-to-quantify aspects of firms' fundamentals. Bozanic et al. (2018) find that managers disclose more non-earnings related forward-looking information when uncertainty is high, resulting in stronger stock price responses and higher accuracy of analyst forecasts. However, if analysts perceive qualitative information as non-verifiable and/or ambiguous when macroeconomic uncertainty increases, they will lower their reliance on it when forecasting future firm risk.¹²

In summary, we predict that the relative importance of quantitative and qualitative information for risk forecasting will depend on how analysts perceive their informativeness during periods of high vs. low macroeconomic uncertainty. If analysts find quantitative/qualitative information in earnings calls to be less (more) informative about future firm risk during periods of increased macroeconomic uncertainty, we expect to find lower (higher) reliance on this information for their risk forecasts. Alternatively, under the null hypothesis, macroeconomic uncertainty does not affect the analysts' forecasting process, i.e., analysts do not change how they use quantitative and qualitative information as a function of overall uncertainty.¹³

¹¹Hutton et al. (2012) find that quantitative management guidance is less accurate "when a firm's fortunes move in concert with broad macroeconomic factors," which is often the case during bad economic times.

¹²See the discussion of verifiability of disclosures in Hutton et al. (2003) and Bozanic et al. (2018).

¹³Observing analysts' forecasts that seem independent of exogenous changes in the economy would be consistent with analysts using the same forecasting model during high vs. low uncertainty times, i.e., basing their risk forecasts solely on past firm-specific experiences. In psychology literature, people's tendencies to over-rely on past experiences, or similarity between stimuli, when making decisions is known as the *representativeness heuristic* (see Kahneman and Tversky (1973)). Making judgments based on the representativeness heuristics allow quick decision making and with less effort. However, it can also lead to more errors. In accounting literature, Johnson (1983) is one of the early applications of the representativeness heuristic in bankruptcy prediction.

3 Sample and Descriptive Statistics

3.1 Matched Sample Procedure

We build our sample by merging two data sources. The first source contains data on analysts' scenario-based valuation estimates from Morgan Stanley analyst reports issued between January 2007 and August 2012 for U.S. publicly listed corporations.¹⁴ The second sample contains quarterly earnings conference call transcripts from www.seekingalpha.com. Founded in 2004, Seeking Alpha has become one of the largest investor-oriented websites in the United States, covering a broad range of publicly-traded companies and providing access to earnings conference call transcripts. We match both samples using company ticker, name and dates of the analyst report and earnings conference call. We match an analyst report with an earnings call transcript if the analyst report is published within ten days of the call date.¹⁵ This procedure results in a matched sample of 3,740 reports, drawn from 609 unique firms and 123 individual analysts, over our sample period. The median firm in our sample has six reports overall and two reports a year.

As an example of analysts' reliance on both quantitative and qualitative information in earnings conference calls, we refer to Figures A1-A2 which include a research note of an analyst report. This note contains a detailed section covering the results discussed during the earnings call. In particular, Figure A1 summarizes "strengths" vs. "weaknesses" as well as "opportunities" vs. "threats," while Figure A2 shows a table where the analyst compares the results of the firm to expectations. This example demonstrates that analysts pay attention to both quantitative financial performance and qualitative management outlook of that performance and future prospects.

¹⁴The individual investment reports that make up our sample are available through sources such as Thomson Financial's Investext database and Bloomberg.

¹⁵In deciding how many days to allow between an earnings call and subsequent analyst report, we want to maximize the number of observations in the sample, while at the same time providing reasonable assurance that the analyst is responding to the earnings call. [Clement et al. \(2011\)](#) find that most analysts issue their revised forecasts within ten days of the earnings announcement.

3.2 Descriptive Statistics

Table 1, Panel A shows that the average *Spread* in our sample is 0.68 with a standard deviation of 0.30, suggesting that our sample exhibits considerable variation in our metric of fundamental risk forecasts. Panel B shows descriptive statistics for variables capturing the quantitative content of earnings conference calls. Earnings conference calls with bad news, *BadNewsInd*, account for around 24% of our sample. Further, around 50% of conference calls contain management *Guidance*, and this guidance is on average optimistic - only 12% of observations have *Guidance* lower than the analyst consensus (see *GuidanceLow*). Also, around 2.2% of all words in the call have financial focus as indicated by *FinTerms*, and on average, around 0.7% of all sentences in the conference call are earnings-related and forward-looking (see *FLS Earnings*). Finally, around 41% of observations experience an earnings forecast *Walkdown* during the quarter preceding the earnings conference call.

Panel C shows that *Tone* of earnings conference calls is, on average, optimistic: the average *Tone* in our sample is 0.54 (standard deviation of 0.60). This descriptive summary is consistent with findings in [Bochkay et al. \(2018\)](#) that earnings call participants tend to use more positive than negative words in their discussions. Further, the mean (standard deviation) of *Uncertainty* and *FLS Other* is 0.93% (0.22%) and 12% (4.14%), indicating a significant variation of these measures in our sample. Finally, an average conference call contains around four questions per analyst as measured by *AnalystQs*.

Table 1 also presents descriptive statistics for a set of control variables that relate to equity risk and analysts' assessments of firm risk (e.g., [Beaver et al. \(1970\)](#); [Fama and French \(1992\)](#); [Lui et al. \(2007\)](#), [Joos et al. \(2016\)](#)). These controls include: firm size, beta, idiosyncratic risk, book-to-market ratio, leverage, earnings volatility, losses, and negative book values. *Size* measures the market value of the firm. *Beta* captures the firm's exposure to systematic market factors. *IdioRisk* captures the firm's sensitivity to idiosyncratic risk. The firm's book-to-market ratio, *BTM*, captures its growth options and level of financial distress. *Leverage* measures the firm's debt relative to the total value of its stock. *EarnVol* measures the volatility of the firm's earnings process. Finally, *Loss* and *NegBV* measure

recent firm financial performance. In addition to these firm characteristics, we also control for *BaseReturn*, which measures the anticipated price appreciation associated with investing in the firm at the time of the analyst report. *BaseReturn* is analogous to the traditional *Target Price* return in prior research (e.g., Bilinski et al. (2012), Bradshaw et al. (2013)). We provide formal definitions and data sources for all variables in Appendix A1.

As reflected in Panel D of Table 1, firms in our sample are large (average market cap is \$8.4bn) and exhibit high growth prospects (average *BTM* is 0.50). Average *Beta* in the sample is 1.20 and average *IdioRisk* of 0.51 points to important idiosyncratic return behavior for the sample observations. Around 14% of the observations are *Loss* firms and about 2% of observations have a negative book value. Average *BaseReturn* is about 15% with a standard deviation of 27%. Finally, Panel D also provides descriptive statistics for the macroeconomic uncertainty variables in our sample. We observe that the average *VIX* value in our sample is around 25, with an interquartile range going from 18 to 27. Also, about 30% of observations in the sample occur during a *Crisis* period as indicated by NBER.

Table 2 presents univariate Pearson correlations between our variables of interest. We observe that *Spread* exhibits strong univariate relations with all variables capturing quantitative and qualitative content in earnings conference calls. Some notable results are the positive relation between *Spread* and *GoodNews* and *BadNews*, as well as *Walkdown*, *Uncertainty* and *FLS Other*. In contrast, *Spread* is negatively related to *Guidance*, *Tone*, *FLS Earnings* and *AnalystQs* in earnings conference calls.

4 Results

This section presents our main empirical results on the relation between analyst forecasts of fundamental risk and metrics of quantitative and qualitative information in earnings calls. Section 4.1 discusses our baseline results, while section 4.2 augments these analyses with a focus on the role of macroeconomic uncertainty. Section 4.3 presents our analysis of the relation between our information metrics and *ex post* absolute valuation errors and stock return volatility.

4.1 Relation between Spread and the Quantitative and Qualitative Information Variables

The univariate correlations in Table 2 provide initial evidence that our variables of quantitative and qualitative information in earnings conference calls relate to the estimates of future firm risk. To control for possible sources of variation in this relation, we estimate the following model:¹⁶

$$\begin{aligned}
 Spread = & \beta_0 + \beta_1 GoodNews + \beta_2 BadNews + \beta_3 BadNewsInd + \beta_4 Guidance + \\
 & \beta_5 GuidanceLow + \beta_6 FinTerms + \beta_7 FLS Earnings + \beta_8 Walkdown + \\
 & \beta_9 Tone + \beta_{10} Uncertainty + \beta_{11} FLS Other + \beta_{12} AnalystQs + B_1 Controls + \\
 & B_2 AnalystFE + B_3 IndustryFE + B_4 YearQuarterFE + \varepsilon,
 \end{aligned} \tag{1}$$

Table 3 reports the results of estimating Eq.(1). Consistent with our predictions, we find that in the full specification of the model both positive and negative earnings surprises map into forecasts of greater future fundamental firm risk as indicated by positive and significant coefficient estimates on *GoodNews* and *BadNews* (coefficients (t-stat.) of 2.363 (2.29) and 3.573 (4.40), respectively). We also find that negative earnings surprises are associated with higher risk forecasts than the positive ones – the coefficient on *BadNewsInd* is positive and significant. Further, *Guidance* obtains a significantly negative coefficient across specifications, indicating that management’s earnings guidance results in lower analysts’ risk forecasts. Next, we find that financially-oriented narrative disclosures map into lower forecasts of future risk as indicated by the negative and significant coefficient on *FinTerms*. We do not find that earnings-related forward-looking disclosures, *FLS Earnings*, help analysts to forecast risk. Finally, the presence of the earnings forecast *Walkdown* is positively associated with analysts’ risk forecasts (coef. of 0.032, t-stat = 4.76), suggesting that declining earnings expectations during the quarter prior to the earnings call increase analysts’ risk perceptions. While we formulated no signed prediction on *Walkdown*, this finding is consistent with re-

¹⁶This model incorporates our quantitative and qualitative variables of interest as well as a set of control variables identified in prior literature (e.g., Lui et al. (2007) and Joos et al. (2016)) and analyst, industry and year-quarter fixed effects. We use the Fama-French 12 industry classification for fixed effects. Our results are the same when we use Fama-French 48 or SIC two-digit industry classifications.

cent evidence in [Bradshaw et al. \(2016\)](#) that forecasting difficulty explains a large portion of the walk-down phenomenon. In our setting, this forecasting difficulty contributes to the increased forecasts of future risk. Overall, these results show that quantitative information in earnings calls is useful for analysts' *risk* forecasts, above and beyond traditional risk metrics.

Turning to our measures of qualitative information, we find a significant and negative coefficient on *Tone*, indicating that more optimistic earnings conference calls are associated with lower forecasts of future fundamental firm risk. Despite a significant positive correlation with *Spread* at the univariate level, the coefficient on *Uncertainty* is not significant in the regression setting. In other words, the effect of language uncertainty or imprecision in earnings calls is not incremental once we control for other firm and earnings call characteristics. We also find that *FLS Other* does not carry relevant new information for analysts' forecasts of fundamental risk. Finally, we find a negative and significant coefficients on *AnalystQs*, suggesting that more questions from analysts during earnings calls reduce future risk estimates. Overall, these results provide evidence on the role of qualitative information, namely earnings call tone and analysts' scrutiny of the call, in the risk forecasting process.

Table 3 further shows that *Spread* is significantly associated with observable firm characteristics related to the riskiness of the firm's operations and long-term value, consistent with [Lui et al. \(2007\)](#) and [Joos et al. \(2016\)](#). In sum, our findings in Table 3 show that measures of both quantitative and qualitative information in earnings calls are relevant for analysts' risk forecasts. In other words, when modeling forecasts of future firm risk, analysts do not just consider traditional risk indicators (e.g., beta, volatility), they also assimilate various quantitative and qualitative information from firm disclosures.

4.2 Role of Macroeconomic Uncertainty

The relation between our information measures and *Spread* can potentially vary with the level of macroeconomic uncertainty at the time of the forecast. We identify conditions of high macroeconomic uncertainty using the CBOE Volatility Index (VIX) and recession periods as indicated by the National Bureau of Economic Research (NBER). Specifically, we create two

indicator variables: *HighVIX*, which is equal to one for observations with VIX higher than the sample median and zero otherwise; and *Crisis*, which is equal to one for observations in the crisis period and zero otherwise.

Table 4 shows descriptive evidence on the behavior of our main variables across sample partitions based on *HighVIX* and *Crisis*. Not surprisingly, the frequency of crisis observations is significantly higher in periods marked by *HighVIX* and, vice versa, the average level of the VIX index is significantly higher in *Crisis* periods. Further, *Spread* is approximately 15% ($0.726/0.632-1$) and 16% ($0.751/0.647-1$) higher for *HighVIX* and *Crisis* observations relative to *LowVIX* and *NoCrisis* observations, respectively. We also observe that the majority of information measures varies across *HighVIX* and *Crisis* sub-samples. For example, there are more negative earnings surprises and forecast walkdowns during *HighVIX* and *Crisis* periods. Similarly, *Tone* is significantly lower, while *Uncertainty* is significantly higher in high macroeconomic uncertainty periods. In contrast, *Guidance* and *AnalystQs* show little variation across different macroeconomic regimes. The descriptive evidence in Table 4 suggests that *HighVIX* and *Crisis* identify periods of challenging forecast circumstances that could affect how analysts use firm-level quantitative and qualitative information to generate their forecasts.

To test whether high macroeconomic uncertainty affects the relation between our measures of quantitative and qualitative information and *Spread*, we estimate a version of Eq.(1) (without year-quarter fixed effects) on sub-samples defined by *HighVIX* and *Crisis*. We then test the differences in coefficients across these sub-samples using the F-test. Panel A of Table 5 reports the analysis for sample partitions based on *HighVIX*. Focusing on the quantitative information measures, we observe that only *FinTerms* exhibits a different relation with *Spread* in low vs. high macroeconomic uncertainty periods. Specifically, the coefficient on *FinTerms* is negative and significant (insignificant) in the low (high) *VIX* periods. This result suggests that while financially-oriented disclosures are relevant to analysts' risk forecasts in low uncertainty times, they are uninformative when macroeconomic uncertainty is high. Interestingly, we find no difference in analysts' reliance on earnings surprise, management

guidance and forecast walkdown measures, i.e., regardless of the level of macroeconomic uncertainty, analysts find these quantitative measures equally useful for fundamental risk forecasting.

Turning to our qualitative measures, we observe a significant difference in the analysts' reliance on *Tone* in low vs. high VIX periods. Specifically, the association between *Tone* and *Spread* is almost three times stronger in high relative to low *VIX* periods (-0.064 vs. -0.022). We do not find any differences in coefficients for other qualitative variables. Overall, these results suggest that despite a variety of qualitative information in earnings calls, analysts find optimistic/pessimistic discussions in earnings calls to be the most informative, and even more so in bad times. The results in Panel B of Table 5, where we use *Crisis* to partition the sample, largely mirror those in Panel A. In addition, we now observe a significant association between *FLS Other* and *Spread* during *Crisis*, while this relation is not significant in non-*Crisis* periods. The prominence of this variable during crisis is consistent with the observation by [Bozanic et al. \(2018\)](#) that *FLS Other* is driven by increased uncertainty.

Our result on analysts' equal reliance on quantitative information during high and low macroeconomic uncertainty times appears to be at odds with the evidence in [Johnson \(1999\)](#) who finds that earnings response coefficients drop during recessions, i.e., investors place lower weight on earnings surprises during bad times. However, as [Johnson \(1999\)](#) points out, recessions also affect investors' risk perceptions, reflected in higher discount rates that vary negatively with earnings response coefficients. In the same vein, we find that analysts' risk forecasts are greater during periods of high macroeconomic uncertainty (see Table 4). Our evidence suggests that quantitative information is associated with these increased risk forecasts. In Section 4.3, we examine whether analysts' equal reliance on quantitative information during high vs. low macroeconomic uncertainty times increases forecast accuracy.

Taken together, the evidence on the role of macroeconomic uncertainty in Tables 4 and 5 leads to three insights. First, heightened levels of macroeconomic uncertainty affect analysts' risk forecasts. Second, analysts generally do not change their reliance on quantitative information in earnings calls during different regimes of macroeconomic uncertainty. Third,

analysts appear to strengthen the assimilation of qualitative information, such as earnings call tone, into their forecasts of fundamental firm risk when macroeconomic uncertainty increases. Overall, these findings are consistent with exogenous changes in aggregate economic activity affecting analysts’ use of quantitative vs. qualitative information.¹⁷

4.3 Mapping of Quantitative and Qualitative Information into Risk Forecasts, Valuation Errors, and Return Volatility

Our analyses in Sections 4.1-4.2 study the relation between quantitative and qualitative information in earnings calls and *ex ante* forecasts of firm risk. We now extend these analyses by examining how the inclusion of quantitative and qualitative information into risk forecasts affects analysts’ forecast accuracy. To answer this question, we use two different outcome variables. First, we study the relation between *Spread* and absolute valuation error, *AbsValErr*, defined as the absolute value of the difference between realized return and predicted base return in the analyst report. Intuitively, if analysts correctly assess state-contingent valuation risk, then *Spread* will be positively associated with the magnitude of ex post absolute valuation errors (Joos et al., 2016). Second, given that return volatility is one of the most commonly used measures of firm risk, we examine the relation between *Spread* and return volatility in the year following the forecast, *FutVolat*.¹⁸ If analysts correctly assess future firm risk, then *Spread* will be positively associated with ex post return volatility.

Given the sequential nature of events in our setting – earnings calls are followed by analyst reports, which in turn are followed by return realizations – we use path analysis to estimate the relation between quantitative and qualitative information in earnings calls and *AbsValErr* and *FutVolat* with a mediating role for *Spread*. Path analysis allows us to differentiate between the direct and indirect (via *Spread*) effects of our earnings call information on subsequent *AbsValErr* and *FutVolat*. Direct effects measure the extent to which *AbsValErr* and *FutVolat* change when earnings call information changes, holding *Spread* fixed. In

¹⁷While our specification in Table 5 includes variables that capture firm-level uncertainty, in untabulated tests we also control for firm-level return volatility. All our inferences remain unchanged.

¹⁸Following Ang et al. (2006), we use the residual stock return of the Fama-French three-factor model to calculate 12 monthly volatility values in the year following the forecast. Then, the annual volatility is the average of these 12 monthly values.

contrast, indirect effects measure the extent to which *AbsValErr* and *FutVolat* change when *Spread* increases or decreases due to changes in earnings call information. In other words, indirect effects measure the extent to which earnings call information contributes to the accuracy of the *Spread* risk forecasts.

Panel A of Table 6 reports the results of our path analysis for the full sample. Consistent with Joos et al. (2016), we find a significant and positive relation between *Spread* and *AbsValErr*, highlighting that increased valuation uncertainty is associated with lower forecast accuracy. Interestingly, we find that none of the quantitative and qualitative information variables has a *direct* effect on *AbsValErr* in the full sample. However, negative earnings surprises (*BadNews*), earnings guidance (*Guidance*), the extent of financial focus in the call (*FinTerms*), forecast walkdown (*Walkdown*), earnings call tone (*Tone*), and the number of analyst questions in the call (*AnalystQs*), relate indirectly to *ex post AbsValErr* through *Spread*. These results suggest that the effects of information variables on *AbsValErr* are fully mediated through analysts' risk forecasts. In other words, analysts seem to correctly incorporate quantitative and qualitative information in earnings calls, increasing the calibration of *Spread* (i.e., tightening the positive relation between *Spread* and *AbsValErr*).

The table further shows a strong positive relation between risk forecasts and *FutVolat*, suggesting that analysts' risk forecasts are also associated with future return fluctuations. Further, we find that positive and negative earnings surprises, earnings call tone, and analysts' questions have both direct and indirect (mediated through *Spread*) effects on future return volatility. In contrast, earnings guidance, financial disclosures, forecast walkdown have only indirect effects on future return volatility. These results suggests that, while analysts' risk forecasts are strong predictors of future return volatility, they do not fully incorporate relevant information from earnings calls.

Next, we examine the role of macroeconomic uncertainty on the relation between quantitative and qualitative information in earnings calls and *AbsValErr* and *FutVolat*, with a mediating role for *Spread*. Similar to Section 4.2, we re-estimate the path analysis using two sub-samples reflecting different levels of macroeconomic uncertainty. For reasons of parsimony,

mony, we use both our proxies for macroeconomic uncertainty simultaneously and partition our sample into a sub-sample of *High Macro Uncertainty* (i.e., $HighVIX=1$ or $Crisis=1$) and a sub-sample of *Low Macro Uncertainty* (i.e., $HighVIX=0$ and $Crisis=0$).

Panels B and C of Table 6 report the results for each sub-sample. We find that *Spread* is almost twice as strongly associated with *AbsValErr* and *FutVolat* in high relative to low uncertainty periods, consistent with analysts' risk forecasts becoming more relevant as macroeconomic uncertainty increases. Further, we find that both *BadNews* and *Tone* exhibit strong direct and indirect effects on *AbsValErr* and *FutVolat* under conditions of *High Macro Uncertainty*. At the same time, their effects on *AbsValErr* and *FutVolat* during *Low Macro Uncertainty* times are either nonexistent or much weaker. For example, the indirect effects of *BadNews* and *Tone* on *AbsValErr* and *FutVolat* are around three ($0.022/0.008$ and $0.032/0.013$) and six ($-0.022/(-0.004)$ and $-0.033/(-0.006)$) times greater, respectively, in the high macro uncertainty period relative to the low one.¹⁹ Observing stronger indirect effects in high macro-uncertainty periods suggests analysts' greater reliance on earning call information (especially qualitative information) during bad times. At the same time, the stronger direct effects for *BadNews* and *Tone* under conditions of high macroeconomic uncertainty also points to analysts not fully incorporating this information in their *Spread* forecasts.

In sum, results of our path analysis are consistent with earnings call information contributing to the calibration of *Spread*, i.e., the strengthening of its relation with *AbsValErr* and its predictive power for *FutVolat*, and even more so in periods of high macroeconomic uncertainty. Similar to our earlier findings, we observe that conditions of macroeconomic uncertainty increase analysts' reliance on quantitative and qualitative information, resulting in better forecasts. More generally, this evidence is consistent with analysts adapting their forecasting models to the changes in the economy.

¹⁹Examining investors' use of information, Williams (2015) documents that investors place a higher weight on bad news when macroeconomic uncertainty is high.

5 Additional Analyses

5.1 Contradictory Signals in Earnings Calls

Our analyses so far show consistent results on the joint role of quantitative and qualitative information as inputs to analysts’ risk forecasts. Out of the variety of measures that we examine across different specifications, we find that earnings surprises (*GoodNews* and *BadNews*) and earnings call tone (*Tone*) are two factors that analysts find the most relevant for risk forecasting. While strongly related, earnings news and earnings call tone often provide “contradictory” signals, i.e., very high (low) earnings surprise is accompanied by not so optimistic (pessimistic) discussion in the earnings call.²⁰ Indeed, the independent sort of our sample into groups based on the distribution of *UE* and *Tone* confirms that around 24% (30%) of low (high) earnings surprise observations have a relatively high (low) *Tone*. In the context of risk forecasting, “contradictory” signals may be of high importance as they point to cases where qualitative disclosures are at odds with the realized financial performance.²¹

To explore the relevance of contradictory signals for analysts’ risk forecasts, we conduct several additional analyses. First, in Table 7 we present descriptive evidence on the average values of *Spread* across terciles of *UE* and *Tone* in Panels A and B, respectively, and on a 2×2 independent sort of observations into *UE* - *Tone* terciles in Panel C. Similar to our results in Section 4.1, we find that analysts map larger earnings surprises into larger estimates of future fundamental risk, regardless of the sign (good vs. bad news). Further, we find that as *Tone* increases, analysts’ forecasts of future fundamental risk decrease. Figure 1 provides graphical evidence on the U-shape relation between *Spread* and *UE* (see part (a)) and the linear relation between *Spread* and *Tone* (see part (b)). Our two-way sort in Panel C shows that *UE* and *Tone* complement each other. For each level of *Tone*, *UE* exhibits

²⁰In our sample, the correlation between the unsigned earnings surprise and earnings call tone is around 17%, significant at the 1% level.

²¹Previous literature has studied how investors respond to confirmatory vs. contradictory performance signals in different settings. An early study by Freeman and Tse (1989) finds stronger price reactions for contradicting news than for confirming news, where contradiction is measured by the current earnings news relative to earnings news in the previous period. More recently, Rees and Sivaramakrishnan (2007) find that both investors and analysts respond more strongly to the earnings surprise when it is simultaneously confirmed by the revenue surprise.

the U-shaped relation with *Spread* we observed earlier in Panel A and Figure 1. In contrast, for each level of *UE*, there is a linear negative relation between *Tone* and *Spread*. These patterns therefore suggest that analysts potentially respond differently to confirmatory vs. contradictory signals in earnings conference calls.

Next, we test the role of confirmatory vs. contradictory signals for analyst risk forecasts in a regression setting by separately estimating a version of Eq.(1) on sub-samples of low and high *UE* (relative to the median).²² For this analysis, we modify Eq.(1) in two ways. First, instead of using a continuous measure of *Tone*, we create two indicator variables *High Tone* and *Low Tone* (based on *Tone* terciles in Table 7).²³ These indicator variables are intended to capture the confirmatory vs. contradictory nature of the tone signal, conditional on the realized performance. In other words, *High Tone* (*Low Tone*) is the contradictory signal in the low (high) *UE* sub-sample, and the confirmatory signal in the high (low) *UE* sub-sample. Also, to recognize the U-shaped relation between *UE* and *Spread* and to control for the magnitude of the earnings surprise in each sub-sample, we include the absolute earnings surprise, *AbsUE*, instead of *GoodNews* and *BadNews* in Eq.(1). Second, we define a measure of potential ambiguity in *Tone*, *Tonal Ambiguity*, which is equal to one if *Tone* is based on the difference of *many* positive and negative words, and zero if *Tone* is based on the difference of *few* positive and negative words (see Appendix A1 for a precise definition). Arguably, netting a large number of positive and negative words conveys a different message in terms of uncertainty than netting a relatively small number of positive and negative words. Put differently, the ambiguity in *Tone* likely increases as the number of tonal words (both positive and negative) to construct it increases.

The results in Table 8 show that contradiction, and not agreement, between signals of earnings surprise and tone affect analysts' future risk estimates. We find that when earnings surprise is low, only the coefficient on *High Tone* is negative and significant, while

²²We partition the sample based on the median of *UE* for exposition purposes and also to increase the power of our tests as the number of observations in our sample is low relative to the number of control variables.

²³By construction, the middle tercile of *Tone* is the control group, i.e., *High Tone* and *Low Tone* measure the degree of optimism and pessimism in earnings conference calls in relative terms.

the coefficient on *Low Tone* is not. In other words, when financial performance is poor, high earnings call tone is associated with low future risk forecasts, while low tone has no effect on forecasts. We find the opposite pattern of results when earnings surprises are high. Specifically, in the presence of performance that surprised on the upside, a negative tone in the earnings call is associated with increased forecasts of future fundamental risk, whereas a positive tone has no effect. These results suggest that analysts consider the tone of earnings conference calls to be a *credible* signal.²⁴ When *Tone* contradicts the earnings surprise signal, analysts consider the qualitative signal to be informative about future risk. When *Tone* simply confirms the quantitative signal, it does not appear to provide new information for risk forecasts. Interestingly, we find that the effect of *Tonal Ambiguity* is positive and significant only for a sub-sample of firms with relatively low earnings surprises. In other words, when an earnings call contains many positive and negative words (i.e., the *Tone* of the call is more ambiguous), analysts perceive this to be an indicator of greater risk in the presence of poor performance.

Overall, the evidence in Tables 7 and 8 show that the presence of contradictory signals affects future risk estimates. When firm earnings surprise is relatively low, positive earnings call tone attenuates future risk estimates, whereas when firm earnings surprise is relatively high, negative earnings call tone exacerbates future risk estimates.

5.2 Revenue vs. Expense Surprises in Earnings Calls

Throughout the analyses, we use earnings surprise as one of the main metrics of quantitative information in earnings calls. However, analysts follow and forecast not just company earnings, but also components of earnings. For example, Figure A2 illustrates that analysts comment on EPS surprise using both revenue and expense surprises. Prior literature also finds that investors respond differently to components of earnings surprises. For instance, [Ertimur et al. \(2003\)](#) find that because of higher persistence investors value revenue surprises more highly than expense surprises. [Gu et al. \(2006\)](#) show that the persistence of earnings

²⁴Focusing on the tone of the language in earnings announcements, [Davis et al. \(2012\)](#) and [Bochkay et al. \(2018\)](#) find results consistent with market participants interpreting the language in earnings press releases and conference calls to be credible, despite potential management opportunism.

surprises varies as a function of whether the underlying revenue and expense components move “in-sync” or not. This evidence, both from practice and academic research, draws attention to the potential separate roles of revenue and expense surprises. Therefore, we next analyze the impact of revenue vs. expense surprises on analysts’ risk forecasts.

We follow [Ertimur et al. \(2003\)](#) and measure revenue surprise as the difference between actual revenues and consensus revenues, scaled by price. Accordingly, expense surprise is the difference between revenue surprise and earnings surprise. Since we have no analyst forecasts of revenues for many of our observations, our sample is reduced to 2,695 observations for this analysis. [Table 9](#) reports the results of estimating [Eq.\(1\)](#) with good and bad revenue and expense surprises instead of good and bad earnings surprises. We find that only the revenue-based surprise is relevant for analyst risk forecasting. Specifically, we find that *Spread* increases as the revenue surprise increases, regardless of the surprise sign (good or bad). These findings are consistent with results in [Ertimur et al. \(2003\)](#) and highlight the greater information value of revenue than expense surprises.

5.3 Generalizability of Results

Our research design relies on estimates generated by analysts from Morgan Stanley. While this research design choice comes with advantages, such as our ability to compute measures of future risk forecasts, it also comes with a limitation that our results are potentially not generalizable. To address this important issue, we conduct an additional analysis using price target forecasts from a broader set of analysts available in IBES. In particular, for each earnings conference call in the sample, we collect all available price target forecasts issued within a 10-day window after the earnings call to construct two measures that broadly mirror our metric of *Spread*, namely *Price Target Dispersion* and *Price Target Range*. If our results generalize to analysts from other brokerage houses, we expect to find similar results for the relations between our measure of quantitative and qualitative information in earnings conference calls and *Price Target Dispersion* and *Price Target Range*.

[Table 10](#) reports the results of using *Price Target Dispersion* and *Price Target Range* as

dependent variables instead of *Spread*.²⁵ Similar to our main results, we observe that earnings surprise, earnings guidance, financially-oriented disclosures, forecast walkdown, earnings call tone, non-earnings related forward-looking statements, and the number of analysts’ questions in the call are significantly associated with the constructed measures of price target dispersion and forecast range. These results support the validity and generalizability of our conclusions for individual analyst’s risk forecasts (i.e., *Spread*). However, it is important to acknowledge that *Spread* differs from *Price Target Dispersion* and *Price Target Range* in an important way. *Spread* is a *within-analyst* measure that holds constant analyst-level attributes at the time of the forecast. By construction, the two other proxies are *between-analyst* metrics that are likely affected by analyst heterogeneity.²⁶ While this feature could affect our findings, the consistency in results across the different specifications, i.e., in Table 3 and Table 10, supports our conclusion that quantitative and qualitative information jointly serve as inputs to analysts’ risk forecasts.

6 Robustness Checks

6.1 Controlling for Past Forecasts of Fundamental Risk

We perform multiple robustness checks to further strengthen our findings. First, we augment our Eq.(1) with a lagged measure of *Spread*, *LagSpread*, taken from the last investment report available prior to the earnings conference call. By including *LagSpread*, we control for the analysts’ risk assessment of a firm at the time of their last forecast update on that firm. In our sample, the number of days between the current analyst report and the last available analyst report prior to the earnings call varies considerably: the mean (median) gap is about 51 (34) days while the first (third) quartile of this distribution is 12 (84) days. Despite this variation in time between reports, it is possible that analysts’ risk assessment, as reflected

²⁵Given that price target forecasts come from multiple analysts, we include the number of analysts as an additional control.

²⁶This feature has led to considerable debate in the literature on whether forecast dispersion captures risk or disagreement (e.g., Johnson (2004)). In a related vein, Joos et al. (2016) discuss why forecast dispersion might not be suitable for measuring analysts’ risk expectations. In untabulated tests, we find that *Spread* and forecast dispersion/range capture different (and incremental) aspects of firm risk as reflected in their strong positive associations with future return volatility.

in *Spread*, does not change much from report to report as it builds on forecasts that are in the tails of the distribution (the *Bull* and the *Bear* cases, respectively). Therefore, in spite of the evidence in [Brown et al. \(2015\)](#) that analysts consider earnings calls highly useful for forecasting, it is important to understand if earnings calls carry information that has not been already reflected in prior risk forecasts.

Table 11 reports the results of controlling for *LagSpread*. The first column shows results for the full sample, allowing a comparison with Table 3. The coefficient on *LagSpread* is positive and highly significant, suggesting a strong relation between analysts' assessments of risk across consecutive reports. Further, we observe that most of our information variables still obtain significant, albeit attenuated, coefficients. As before, we find that *BadNews* and *Walkdown* increase *Spread*, while *Guidance*, *FinTerms*, and *Tone* decrease *Spread*. Different from the findings in Table 3, *GoodNews* becomes insignificant and *GuidanceLow* is now positive and significant. The last two columns in Table 11 introduce *LagSpread* in periods of *Low* and *High Macroeconomic Uncertainty*, similar to Table 5. In both time periods, we generally observe similar results for our quantitative variables of interest, although the effects are stronger during high macro-uncertainty times. In contrast, our qualitative variables *Tone* and *Uncertainty* are only significant when macroeconomic uncertainty is high. Taken together, these results corroborate our earlier findings that analysts map both quantitative and qualitative information into their estimates of fundamental risk. Importantly, the results also support our earlier finding that qualitative information, such as earnings call *Tone*, is an important input to analysts' risk forecasts during times of high macroeconomic uncertainty.

6.2 Alternative Measures of Earnings Conference Call Tone

Out of all qualitative measures examined, *Tone* exhibits the strongest and consistent relation with analysts' risk forecasts. While *Tone* captures a relevant feature of earnings calls, this single variable presents some limitations which we address in additional robustness checks. First, we distinguish between *Tone* of different parts of an earnings call, namely the management prepared remarks part and the Q&A part. In untabulated tests, we find that *Tone*

of both sections of the earnings call is useful for analysts' risk forecasting. This result is important given the evidence in [Mayew et al. \(2013\)](#) that analysts participating in earnings calls possess superior private information relative to those that do not participate. If participating analysts possess strong priors about future firm risk, then tone of their participation will partially set the tone of the entire conference call. Our evidence though shows that *Tone* of management prepared remarks, which precede analysts' participation in the call, is associated with analysts' risk forecasts, thereby alleviating potential concerns of reverse causality between *Tone* and *Spread*.²⁷

Second, our measure of *Tone* is the difference between the frequency of positive and negative words in the earnings call. However, positive words are often used to frame a negative statement ([Loughran and McDonald, 2016](#)). Therefore, we split our *Tone* variable into its positive (*PosTone*) and negative (*NegTone*) components and re-estimate Eq.(1) using *PosTone* and *NegTone* instead of *Tone*. We find that the coefficient on *PosTone* (*NegTone*) is negative (positive) and significant. We also find similar results when we account for negations in text (e.g., not good, no improvement). These findings support and extend our earlier results on the directional negative relation between *Tone* and risk forecasts. Consistent with findings on investor reactions to positive vs. negative language in [Tetlock \(2007\)](#) and [Bochkay et al. \(2018\)](#), we find that *both* positive and negative language is informative to analysts. These findings also speak to results in [Mayew and Venkatachalam \(2012\)](#), who examine positive and negative managerial affective states in earnings calls. In the context of recommendation changes, [Mayew and Venkatachalam \(2012\)](#) find that analysts incorporate positive, but not negative affect into recommendation changes and relate this pattern to the asymmetry in analysts' incentives. In our setting, we find that both positive and negative tone is associated with risk forecasts, suggesting that risk forecasts are free of incentive biases as documented in [Joos et al. \(2016\)](#).

²⁷In untabulated tests, we also differentiate between *Tone* of management and participating analysts in the Q&A section of the call. We find that the tone of both parties during the Q&A part is associated with analysts' risk forecasts.

7 Conclusion

In this paper, we use a sample of scenario-based investment reports to examine how analysts incorporate quantitative and qualitative information from earnings calls into forecasts of fundamental firm risk. We find that analysts’ perceptions of future firm risk increase in the magnitude of the earnings surprise (of either) and in the presence of the earnings forecast walkdown. Further, we find that analysts’ perceptions of firm risk decrease when managers provide earnings guidance and financially-oriented information, when earnings call tone is more optimistic, and when analysts ask more questions during the call. When examining analysts’ risk perceptions across time, we find that the relative importance of qualitative information increases during times of high macroeconomic uncertainty, while the importance of quantitative information remains the same. This increased reliance on qualitative information improves the calibration of risk forecasts during high macroeconomic uncertainty times. Additionally, we document that analysts respond to ‘contradictory’ signals in earnings calls and find revenue surprises more relevant for risk forecasting than expense surprises. Our results are robust to alternative research designs and variable measurements.

In sum, our evidence that both quantitative and qualitative information in earnings calls matters for analysts’ risk forecasts both resonates with and complements the survey evidence in [Brown et al. \(2015\)](#) on the importance of earnings conference calls to analyst research. Importantly, our findings on the relevance of conditions of macroeconomic uncertainty highlight that to understand “what analysts do” research needs to consider aspects of the forecast setting beyond particular strategic incentives or behavioral biases that affect analysts’ forecast activities. We thus contribute to the literature that aims to open the “black box” of the analyst forecasting process. Similar to [Bradshaw et al. \(2016\)](#) and [Loh and Stulz \(2018\)](#), we believe that future research can explore further what aspects of the forecast setting make the analyst forecasting job “difficult” and what actions analysts take to mitigate this difficulty.

References

- Amiram, D., W. R. Landsman, E. L. Owens, and S. R. Stubben (2017). How are analysts' forecasts affected by high uncertainty? *Journal of Business Finance & Accounting* 45(3-4), 295–318.
- Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang (2006). The cross-section of volatility and expected returns. *The Journal of Finance* 61(1), 259–299.
- Arand, D. and A. G. Kerl (2012). Analyst research and investor reactions: Evidence from the 2008 financial crisis. *Working Paper, University of Giessen*.
- Asquith, P., M. M. Mikhail, and A. S. Au (2005). Information content of equity analyst reports. *Journal of Financial Economics* 75, 245–282.
- Baginski, S. P., E. J. Conrad, and J. M. Hassell (1993). The effects of management forecast precision on equity pricing and on the assessment of earnings uncertainty. *The Accounting Review*, 913–927.
- Barron, O. E., D. Byard, and Y. Yu (2008). Earnings surprises that motivate analysts to reduce average forecast error. *The Accounting Review* 83(2), 303–325.
- Bartov, E., D. Givoly, and C. Hayn (2002). The rewards to meeting or beating earnings expectations. *Journal of Accounting and Economics* 33(2), 173–204.
- Beaver, W., P. Kettler, and M. Scholes (1970). The association between market determined and accounting determined risk measures. *The Accounting Review* 45(4), 654–682.
- Bilinski, P., D. Lyssimachou, and M. Walker (2012). Target price accuracy: International evidence. *The Accounting Review* 88(3), 825–851.
- Bloom, N. (2009). The impact of uncertainty shocks. *Econometrica* 77(3), 623–685.
- Bochkay, K., S. Chava, and J. Hales (2018). Hyperbole or reality? Investor response to extreme language in earnings conference calls. *Working Paper, University of Miami*.
- Bozanic, Z., D. T. Roulstone, and A. Van Buskirk (2018). Management earnings forecasts and other forward-looking statements. *Journal of Accounting and Economics* 65, 1–20.
- Bradshaw, M. T. (2011). Analysts' forecasts: What do we know after decades of work? *Working Paper, Boston College*.
- Bradshaw, M. T., L. D. Brown, and K. Huang (2013). Do sell-side analysts exhibit differential target price forecasting ability? *Review of Accounting Studies* 18(4), 930–955.
- Bradshaw, M. T., L. F. Lee, and K. Peterson (2016). The interactive role of difficulty and incentives in explaining the annual earnings forecast walkdown. *The Accounting Review* 91(4), 995–1021.

- Bradshaw, M. T., X. Wang, and D. Zhou (2017). Soft information in the financial press and analysts' recommendation revisions. *Working Paper, Boston College*.
- Brown, L. D., A. C. Call, M. B. Clement, and N. Y. Sharp (2015). Inside the "black box" of sell-side financial analysts. *Journal of Accounting Research* 53(1), 1–47.
- Campbell, J., H. Chen, D. Dhaliwal, H.-M. Lu, and L. Steele (2014). The information content of mandatory risk factor disclosures in corporate filings. *Review of Accounting Studies* 19(1), 396–455.
- Campbell, J., H. S. Lee, H.-M. Lu, and L. Steele (2017). Unexpected disclosure tone volatility and investor risk assessmentf. *Working paper, University of Georgia*.
- Chen, H., P. De, Y. J. Hu, and B.-H. Hwang (2014). Wisdom of crowds: the value of stock opinions transmitted through social media. *Review of Financial Studies* 27(5), 1367–1403.
- Clement, M., R. Frankel, and J. Miller (2003). Confirming management earnings forecasts, earnings uncertainty, and stock returns. *Journal of Accounting Research* 41(4), 653–679.
- Clement, M. B., J. Hales, and Y. Xue (2011). Understanding analysts' use of stock returns and other analysts' revisions when forecasting earnings. *Journal of Accounting and Economics* 51(3), 279–299.
- Cotter, J., I. Tuna, and P. D. Wysocki (2006). Expectations management and beatable targets: How do analysts react to explicit earnings guidance? *Contemporary Accounting Research* 23(3), 593–624.
- D'Aurizio, L., T. Olivero, and L. Romano (2015). Family firms, soft information and bank lending in a financial crisis. *Journal of Corporate Finance* 33, 279–292.
- Davis, A. K., J. M. Piger, and L. M. Sedor (2012). Beyond the numbers: Measuring the information content of earnings press release language. *Contemporary Accounting Research* 29(3), 845–868.
- Diamond, D. W. and R. E. Verrecchia (1991). Disclosure, liquidity, and the cost of capital. *The Journal of Finance* 46(4), 1325–1359.
- Ertimur, Y., J. Livnat, and M. Martikainen (2003). Differential market reactions to revenue and expense surprises. *Review of Accounting Studies* 8, 185–211.
- Fama, E. F. and K. R. French (1992). The cross-section of expected stock returns. *The Journal of Finance* 47(2), 427–465.
- FINRA (2014). Research analysts and research reports. *Rule 2241*.
- Freeman, R. N. and S. Tse (1989). The multiperiod information content of accounting earnings: Confirmations and contradictions of previous earnings reports. *Journal of Accounting Research* 27, 49–79.

- Garcia, D. (2013). Sentiment during recessions. *The Journal of Finance* 68(3), 1267–1300.
- Gu, Z., P. C. Jain, and S. Ramnath (2006). In-sync or out-of-sync? the joint information in revenues and expenses. *Working Paper*.
- Hollander, S., M. Pronk, and E. Roelofsen (2010). Does silence speak? An empirical analysis of disclosure choices during conference calls. *Journal of Accounting Research* 48(3), 531–563.
- Hope, O.-K., D. Hu, and H. Lu (2016). The benefits of specific risk-factor disclosures. *Review of Accounting Studies* 21(4), 1005–1045.
- Huang, A., R. Lehavy, A. Zang, and R. Zheng (2017). Analyst information discovery and information interpretation roles: a topic modeling approach. *Management Science*.
- Hutton, A. P., L. F. Lee, and S. Z. Shu (2012). Do managers always know better? The relative accuracy of management and analyst forecasts. *Journal of Accounting Research* 50(5), 1217–1244.
- Hutton, A. P., G. S. Miller, and D. J. Skinner (2003). The Role of Supplementary Statements with Management Earnings Forecasts. *Journal of Accounting Research* 41(5), 867 – 890.
- Johnson, M. F. (1999). Business cycles and the relation between security returns and earnings. *Review of Accounting Studies* 4(2), 93–117.
- Johnson, T. C. (2004). Forecast dispersion and the cross-section of expected returns. *The Journal of Finance* 59(5), 1957–1978.
- Johnson, W. B. (1983). “Representativeness” in judgmental predictions of corporate bankruptcy. *The Accounting Review* 58, 78–97.
- Joos, P. and J. D. Piotroski (2017). The best of all possible worlds: Unraveling target price optimism using analysts’ scenario-based valuations. *Review of Accounting Studies* 22, 1492–1540.
- Joos, P., J. D. Piotroski, and S. Srinivasan (2016). Can analysts assess fundamental risk and valuation uncertainty? An empirical analysis of scenario-based value estimates. *Journal of Financial Economics* 121(3), 645–663.
- Kahneman, D. and A. Tversky (1973). On the psychology of prediction. *Psychological review* 80(4), 237.
- Klarman, S. A. (1991). *Margin of safety: risk-averse value investing strategies for the thoughtful investor*. HarperBusiness.
- Kothari, S., X. Li, and J. Short (2009). The effect of disclosures by management, analysts, and business press on cost of capital, return volatility, and analyst forecasts: A study using content analysis. *The Accounting Review* 84(5), 1639–1670.

- Kothari, S., E. So, and R. Verdi (2016). Analysts' forecasts and asset pricing: A survey. *Annual Review of Financial Economics* 8, 197–219.
- Kravet, T. and V. Muslu (2013). Textual risk disclosures and investors' risk perceptions. *Review of Accounting Studies* 18(4), 1088–1122.
- Loh, R. K. and R. M. Stulz (2018). Is sell-side research more valuable in bad times? *The Journal of Finance* 73(3), 959–1013.
- Loughran, T. and B. McDonald (2011). When is a liability not a liability? *The Journal of Finance* 66(1), 35 – 65.
- Loughran, T. and B. McDonald (2016). Textual analysis in accounting and finance: A survey. *Journal of Accounting Research* 54(4), 1187–1230.
- Lui, D., S. Markov, and A. Tamayo (2007). What makes a stock risky? Evidence from sell-side analysts' risk ratings. *Journal of Accounting Research* 45(3), 629–665.
- Lui, D., S. Markov, and A. Tamayo (2012). Equity analysts and the market's assessment of risk. *Journal of Accounting Research* 50(5), 1287–1317.
- Marsh, L. C. and D. R. Cormier (2001). *Spline regression models*, Volume 137. Sage.
- Matsumoto, D., M. Pronk, and E. Roelofsen (2011). What makes conference calls useful? The information content of managers' presentations and analysts' discussion sessions. *The Accounting Review* 86(4), 1383–1414.
- Matsumoto, D. A. (2002). Management's incentives to avoid negative earnings surprises. *The Accounting Review* 77(3), 483–514.
- Mayew, W. J., N. Sharp, and M. Venkatachalam (2013). Using earnings conference calls to identify analysts with superior private information. *Review of Accounting Studies* 18(3), 386–413.
- Mayew, W. J. and M. Venkatachalam (2012). The power of voice: Managerial affective states and future firm performance. *The Journal of Finance* 67(1), 1–43.
- Ng, J., R. Verrecchia, and J. Weber (2009). Firm performance measures and adverse selection. *Working paper, MIT Sloan School of Management*.
- Ramnath, S., S. Rock, and P. Shane (2008). The financial analyst forecasting literature: A taxonomy with suggestions for further research. *International Journal of Forecasting* 24(1), 34–75.
- Rees, L. and K. Sivaramakrishnan (2007). The effect of meeting or beating revenue forecasts on the association between quarterly returns and earnings forecast errors. *Contemporary Accounting Research* 24(1), 259–290.

- Richardson, S., S. H. Teoh, and P. D. Wysocki (2004). The walk-down to beatable analyst forecasts: The role of equity issuance and insider trading incentives. *Contemporary Accounting Research* 21(4), 885–924.
- Simonsohn, U. (2018). Two-lines: A valid alternative to the invalid testing of u-shaped relationships with quadratic regressions. *Working Paper, available at SSRN: <https://ssrn.com/abstract=3021690>*.
- Skinner, D. J. and R. G. Sloan (2002). Earnings surprises, growth expectations, and stock returns or don't let an earnings torpedo sink your portfolio. *Review of Accounting Studies* 7(2-3), 289–312.
- Sobel, M. E. (1987). Direct and indirect effects in linear structural equation models. *Sociological Methods & Research* 16(1), 155–176.
- Srinivasan, S. and D. Lane (2011). The risk-reward framework at Morgan Stanley research. *Harvard Business School Case 111-011*.
- Tetlock, P. C. (2007). Giving content to investor sentiment: the role of media in the stock market. *The Journal of Finance* 62(3), 1139 – 1167.
- Tetlock, P. C., M. Saar-Tsechansky, and S. Macskassy (2008). More than words: Quantifying language to measure firms' fundamentals. *The Journal of Finance* 63(3), 1437 – 1467.
- Weyns, G., J.-L. Perez, and V. Jenkins (2007). Risk-reward views: Unlocking the full potential of fundamental analysis. *Morgan Stanley Global Research*.
- Williams, C. D. (2015). Asymmetric responses to earnings news: A case for ambiguity. *The Accounting Review* 90(2), 785–817.
- Zmijewski, M. (1993). Comments on earnings forecasting research: its implications for capital markets research' by L. Brown. *International Journal of Forecasting* 9, 337–342.

Appendix

Table A1: Variable Definitions and Data Sources.

| Variable | Definition/Source |
|---------------------|---|
| <i>Spread</i> | Analyst’s <i>Bull</i> forecast minus <i>Bear</i> forecast scaled by the average of <i>Bull</i> and <i>Bear</i> . Data Source: Morgan Stanley. |
| <i>AbsValErr</i> | Absolute value of the firm’s realized raw return one year after the analyst report minus the predicted return under the analyst’s base-case scenario (i.e., <i>BaseReturn</i>). Data Source: Morgan Stanley, CRSP. |
| <i>FutVolat</i> | Volatility of the residual return from the Fama-French three-factor model (as in Ang et al. (2006)) in the year following the analyst report, calculated as the average of monthly volatility values. Data Source: CRSP. |
| <i>UE</i> | Actual earnings per share minus analyst consensus forecast of one- or two-quarters-ahead earnings issued or reviewed in the last 60 days before the earnings announcement divided by stock price at the end of quarter, winsorized at 1% and 99%. Data Source: IBES. |
| <i>AbsUE</i> | Absolute value of <i>UE</i> . Data Source: IBES. |
| <i>GoodNews</i> | Equals to <i>UE</i> if $UE \geq 0$, and 0 otherwise. Data Source: IBES. |
| <i>BadNews</i> | Equals to $ UE $ if $UE < 0$, and 0 otherwise. Data Source: IBES. |
| <i>BadNewsInd</i> | Indicator variable that equals to 1 if <i>UE</i> is lower than 0. Data Source: IBES. |
| <i>Guidance</i> | Indicator variable equal to 1 if a firm has issued an earnings guidance during the 5-day window of the earnings announcement and 0 otherwise. Data Source: IBES. |
| <i>GuidanceLow</i> | Indicator variable equal to 1 if management earnings guidance is lower than the analyst consensus forecast. Data Source: IBES. |
| <i>Walkdown</i> | Indicator variable equal to 1 if the consensus forecast used to calculate <i>UE</i> is lower than the consensus forecast available after the previous quarter earnings announcement. Data Source: IBES. |
| <i>Tone</i> | Difference between positive and negative word counts scaled by total words in the earnings conference call ($\times 100$). Positive and negative words are identified using Loughran and McDonald (2011) ’s dictionary. Data Source: www.seekingalpha.com . |
| <i>Uncertainty</i> | Number of uncertain words in the earnings conference call, scaled by total words in the earnings conference call ($\times 100$). Uncertain words are identified using Loughran and McDonald (2011) ’s dictionary. Data Source: www.seekingalpha.com . |
| <i>FLS Earnings</i> | Number of earnings-related forward-looking sentences in the earnings conference call (following the methodology in Bozanic et al. (2018)), scaled by the number of all sentences in the conference call. Data Source: www.seekingalpha.com . |
| <i>FLS Other</i> | Number of non-earnings-related forward-looking sentences in the earnings conference call (following the methodology in Bozanic et al. (2018)), scaled by the number of all sentences in the conference call. Data Source: www.seekingalpha.com . |

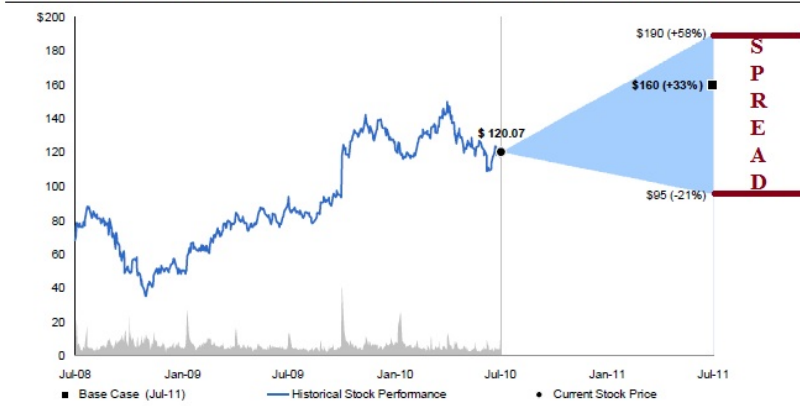
Table A1: Variable Definitions and Data Sources, continued

| Variable | Definition/Source |
|--------------------------------|---|
| <i>FinTerms</i> | Number of financially-oriented words in the earnings conference call, scaled by the number of all words in the conference call. Financially-oriented words are identified following Matsumoto et al. (2011) . Data Source: www.seekingalpha.com . |
| <i>AnalystQs</i> | Number of analysts' questions in the earnings conference call, scaled by the number of analysts following the firm. Data Source: www.seekingalpha.com . |
| <i>Tonal Ambiguity</i> | Indicator variable equal to 1 if the proportion of positive and negative words (relative to all words in the earnings conference call) are in the top five deciles of the respective distributions, and 0 otherwise. Data Source: www.seekingalpha.com . |
| <i>FirmSize</i> | Natural logarithm of the market value of equity at the end of the previous quarter. Data Source: COMPUSTAT. |
| <i>BTM</i> | Ratio of common equity to market value of the firm. Data Source: COMPUSTAT. |
| <i>Leverage</i> | Long-term debt to total assets ratio. Data Source: COMPUSTAT. |
| <i>Loss</i> | Indicator variable equal to one if the sum of the past four quarterly earnings is negative, and zero otherwise. Data Source: COMPUSTAT. |
| <i>EarnVol</i> | Standard deviation of firm earnings, calculated using earnings scaled by total assets in the last twenty quarters, with a minimum of eight quarters required. Data Source: COMPUSTAT. |
| <i>IdioRisk</i> | Natural log of the ratio $(1 - R^2)/R^2$ where R^2 is the R^2 from a regression of weekly firm-returns on the weekly S&P500 returns, measured over the 52-week interval before release of the analyst report. Data Source: CRSP. |
| <i>Beta</i> | Beta of the firm relative to the S&P500, measured as the slope in a weekly return regression over the 60 weeks before the release of the analyst report. Data Source: CRSP. |
| <i>BaseReturn</i> | The expected return (excluding dividends) of investing in the firm at the time of the analyst report, measured as <i>Base</i> minus <i>Price</i> scaled by <i>Price</i> , where <i>Price</i> is the closing stock price on the day before the release of the analyst report. Data Source: Morgan Stanley, CRSP. |
| <i>NegBV</i> | Indicator variable equal to one if common equity is negative, and zero otherwise. Data Source: COMPUSTAT. |
| <i>VIX</i> | Market volatility index seven days prior to the analyst report. Data Source: CBOE. |
| <i>High VIX</i> | Indicator variable that equals to 1 if <i>VIX</i> is greater than the sample median of 21.734. Data Source: CBOE. |
| <i>Crisis</i> | Indicator variable equal to 1 if earnings conference call and analyst report are at the time of 2007-2009 financial crisis. Data Source: NBER. |
| <i>Price Target Dispersion</i> | Coefficient of Variation of all target price forecasts issued within a 10-day window after the earnings announcement. Data Source: IBES. |
| <i>Price Target Range</i> | Range scaled by the mid-point of all target price forecasts issued within a 10-day window after the earnings announcement. Data Source: IBES. |

Figure A1: Example of Scenario-based Valuation at Morgan Stanley

Amazon.com (AMZN, \$120, OW, DCF \$160)

Risk-Reward View: Customer Focus Drives Sustainable Growth



Source: FactSet, Morgan Stanley Research

| | | | |
|------------------|-------------------------------|-------|--|
| Bull Case | 22x Bull Case 11E EV / EBITDA | \$190 | Assumes Amazon.com actively participates in digital distribution of video, music, and books. Amazon.com continues to add products / selection and gain share as traditional retailers suffers. Assumes 5-yr. revenue CAGR (C09-C14E) of 25% and cash operating margin expands to 9.3% in C2019E. |
| Base Case | 20x Base Case 11E EV / EBITDA | \$160 | Assumes Amazon.com's invests in infrastructure in C2010, but margins rebound in C2011E + C2012E. Momentum continues as customers value broad selection of attractively priced items, which allows Amazon.com revenue to significantly outperform overall eCommerce. Digital distribution impacts business and Kindle continues to face challengers, but Amazon.com is able to participate in the digital transition. Assumes 5-yr. revenue CAGR (C09-C14E) of 22% and cash operating margin expands to 9% in C2019E. |
| Bear Case | 16x Bear Case 11E EV / EBITDA | \$95 | Business slows as digital distribution negatively impacts sales of media and intense competition hurts Amazon.com's competitive position in the digital media transition (Music, Video, Books). Assumes 5-yr. revenue CAGR (C09-C14E) of 18% and cash operating margin remains around 7% in C2019E. |

SWOT Analysis – Amazon.com

| | |
|---|---|
| Strengths <ol style="list-style-type: none"> Market / brand leadership in growing eCommerce Best-in-class user experience defined by selection / convenience / reliability / low prices / free shipping / powerful recommendation engine Leader in Internet innovation + logistics | Weaknesses <ol style="list-style-type: none"> Low prices / free shipping / product mix pressure near-term margins High exposure to foreign exchange fluctuations Seasonality + inventory risk |
| Opportunities <ol style="list-style-type: none"> Continued share gains in overall retail market, in which eCommerce penetration is still low. Continued expansion into international markets (both mature + emerging) Monetization of nascent-stage initiatives gaining traction, such as Kindle, Amazon.com Web Services + digital downloads (VoD + Amazon.comMP3) | Threats <ol style="list-style-type: none"> Apple and others present threat as media products transition to digital distribution Execution risk in new markets / categories / products Intense competition in both core (retail) + new markets (digital downloads, eCommerce solutions, web services, etc.) Legal (e.g., state sales tax issues, international sales tax possibility) |

Source: Morgan Stanley Research, Format based on Michael Porter's *Competitive Strategy*

Source: Morgan Stanley research, 23 July 2010. Amazon.com. CQ2: Strong revenue, increased investment.

Why Overweight?

- eCommerce leader that continues to take market share from offline and online channels
- Broad selection / best-in-class customer experience / ease of use creates superior user experience and drives loyalty
- Focus on customer has led to double-digit Y/Y active customer / seller growth

Key Value Drivers

- Active customers eclipsed 118MM (+26% Y/Y) in CQ2 and further customer growth should drive future revenue growth
- Amazon.com / Kindle app downloads
- Increased revenue per customer and higher ASPs drive increased value

Potential Catalysts

- Accelerating mobile commerce business (3.5% of TTM revenue / currently 5%+ per our estimate) and mobile commerce share could be higher than its eCommerce share
- Faster-than-expected shift from offline to online commerce
- Retail bankruptcies could continue to shift sales online

Potential Risks

- Amazon.com faces competitive threat from Apple / others as Media sales (44% of total revenue in CQ2) transition to digital distribution
- Investors capitalize working capital free cash at the same rate as operating free cash; if growth slows, this could have a meaningful impact on the stock
- Sales tax collection laws could be challenged as eCommerce grows

Figure A2: Example of Scenario-based Valuation at Morgan Stanley

AMZN — CQ2:10E vs. CQ2:10A Snapshot

(US\$ in Thousands, Except per Share Data)

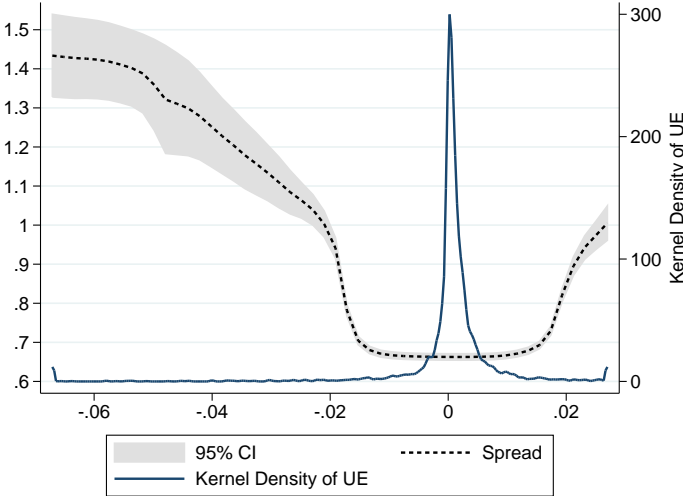
| | 6/10E | 6/10A | Comments |
|---|--------------------|--------------------|--|
| Revenue | \$6,497,610 | \$6,566,000 | 1% above our estimate; +41% Y/Y (+42% ex. FX), vs. +14% in CQ2:09 |
| Media | 2,923,100 | 2,874,000 | |
| Electronics & Other General Merchandise | 3,379,230 | 3,489,000 | First time EGM revenue 50%+ of total revenue; +69% Y/Y |
| Other | 195,280 | 203,000 | |
| North America | \$3,627,170 | \$3,590,000 | 1% below our estimate; +46% Y/Y vs. +13% Y/Y in CQ2:09 |
| Media | 1,435,000 | 1,324,000 | |
| Electronics & Other General Merchandise | 2,029,770 | 2,090,000 | |
| Other | 162,400 | 176,000 | |
| International | \$2,870,440 | \$2,976,000 | 4% above our estimate; +35% Y/Y vs. +16% Y/Y in CQ2:09; +38% ex. FX |
| Media | 1,488,100 | 1,550,000 | |
| Electronics & Other General Merchandise | 1,349,460 | 1,399,000 | |
| Other | 32,880 | 27,000 | |
| Company Revenue Guidance | \$6.10-6.70B | \$6.10-6.70B | |
| Cost of Revenue | 4,921,362 | 4,957,000 | COGS growth in line with revenue growth at +41% Y/Y |
| North America | 2,630,881 | 2,570,000 | |
| International | 2,290,481 | 2,387,000 | |
| Gross Profit (incl. Depreciation) | \$1,576,248 | \$1,609,000 | Gross margin of 24.5%; in-line with our 24.3% estimate; vs. 24.4% in CQ2:09 |
| North America | 996,289 | 1,020,000 | |
| International | 579,959 | 589,000 | |
| Marketing | 519,809 | 558,000 | |
| Fulfillment | 185,182 | 204,000 | |
| Technology & Content | 344,373 | 350,000 | |
| General & Administrative | 81,220 | 91,000 | |
| Other Operating Expense | 25,000 | 25,000 | |
| Total Stock Compensation Expense | 106,250 | 111,000 | |
| Total Operating Expenses (incl. Amort. Stock Comp.) | \$1,261,834 | \$1,339,000 | |
| Total Operating Expenses (excl. Amort. Stock Comp.) | \$1,130,584 | \$1,203,000 | |
| Operating Income (incl. Stock Comp. & Other) | \$314,414 | \$270,000 | |
| Operating Income (excl. Stock Comp. & Other) | \$445,664 | \$406,000 | Operating margin of 6.2%, below our 6.9% estimate on higher marketing and fulfillment expenses |
| Company Operating Income (incl. Stock Comp.) Guidance | \$220-320MM | | |
| Company Operating Income (excl. Stock Comp.) Guidance | \$350-450MM | | |
| EBITDA (excl. Stock Comp. & Other) | \$77,008 | \$35,000 | |
| Net Interest (Income) and Other (Income) | (2,199) | (27,000) | |
| Pre-Tax Profit (excl. Stock Comp. & Other) | \$423,862 | \$408,000 | |
| Provision / (Benefit) for Income Taxes | 79,153 | 88,000 | |
| Adjustment for Extraordinary Items- Reported | 0 | 0 | |
| Tax benefit from Stock Compensation | 37,188 | 38,850 | |
| (Benefit) for NOL Carryforwards | 0 | 0 | |
| Operating Net Income (excl. Stock Comp. & Other) | \$306,522 | \$281,150 | |
| Company Operating Net Income Guidance | | | |
| Reported Net Income | \$237,459 | \$207,000 | |
| Wtd. Avg. Shares Out (Diluted) | 451,013 | 455,000 | |
| Operating EPS (excl. Stock Comp. & Other) | \$0.68 | \$0.62 | |
| Reported EPS | 0.63 | 0.45 | Below our estimate due to revenue higher-than-expected opex; taxes \$0.04 negative impact to EPS. |

Source: Morgan Stanley research, 23 July 2010. Amazon.com. CQ2: Strong revenue, increased investment.

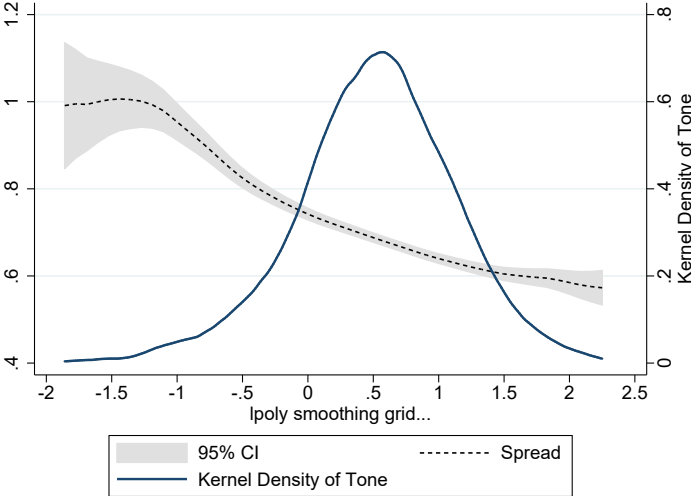
Figures and Tables

Figure 1: Analysts' Forecasts of Future Risk following Earnings Conference Calls.

(a) Local polynomial smooth of Spread on UE



(b) Local polynomial smooth of Spread on Tone



This figure plots kernel densities of *UE* (part a) and *Tone* (part b) with the local polynomial smoothing of *Spread* on *UE* and *Tone*, respectively.

Table 1: Descriptive Statistics

| | Mean | Median | STD | Q1 | Q3 |
|--|---------|---------|---------|---------|---------|
| Panel A: Outcome Variables | | | | | |
| <i>Spread</i> | 0.6794 | 0.6117 | 0.2959 | 0.4758 | 0.8125 |
| <i>AbsValErr</i> | 0.3469 | 0.2607 | 0.3135 | 0.1169 | 0.4807 |
| <i>FutVolat</i> | 0.0202 | 0.0173 | 0.0113 | 0.0123 | 0.0251 |
| Panel B: Quantitative Variables | | | | | |
| <i>GoodNews</i> | 0.0022 | 0.0007 | 0.0049 | 0.0000 | 0.0021 |
| <i>BadNews</i> | 0.0017 | 0.0000 | 0.0081 | 0.0000 | 0.0000 |
| <i>BadNewsInd</i> | 0.2417 | 0.0000 | 0.4282 | 0.0000 | 0.0000 |
| <i>Guidance</i> | 0.5021 | 1.0000 | 0.5001 | 0.0000 | 1.0000 |
| <i>GuidanceLow</i> | 0.1238 | 0.0000 | 0.3294 | 0.0000 | 0.0000 |
| <i>FinTerms</i> | 0.0220 | 0.0209 | 0.0074 | 0.0171 | 0.0259 |
| <i>FLS Earnings</i> | 0.0070 | 0.0055 | 0.0063 | 0.0023 | 0.0100 |
| <i>Walkdown</i> | 0.4048 | 0.0000 | 0.4909 | 0.0000 | 1.0000 |
| Panel C: Qualitative Variables | | | | | |
| <i>Tone</i> | 0.5402 | 0.5540 | 0.6001 | 0.1772 | 0.9254 |
| <i>Uncertainty</i> | 0.9323 | 0.9196 | 0.2267 | 0.7752 | 1.0661 |
| <i>FLS Other</i> | 0.1203 | 0.1156 | 0.0414 | 0.0896 | 0.1456 |
| <i>AnalystQs</i> | 4.0547 | 2.6000 | 5.4349 | 1.6667 | 4.2857 |
| Panel D: Control Variables | | | | | |
| <i>FirmSize</i> | 9.0419 | 9.0518 | 1.4628 | 8.0775 | 9.9825 |
| <i>BTM</i> | 0.5022 | 0.3868 | 0.4401 | 0.2351 | 0.6579 |
| <i>Leverage</i> | 2.9041 | 1.4001 | 4.6812 | 0.6292 | 3.2178 |
| <i>Loss</i> | 0.1404 | 0.0000 | 0.3474 | 0.0000 | 0.0000 |
| <i>EarnVol</i> | 0.0197 | 0.0096 | 0.0290 | 0.0050 | 0.0210 |
| <i>Beta</i> | 1.2057 | 1.1532 | 0.5267 | 0.8504 | 1.4865 |
| <i>IdioRisk</i> | 0.5154 | 0.3950 | 1.0049 | -0.1654 | 1.0503 |
| <i>BaseReturn</i> | 0.1491 | 0.1182 | 0.2712 | 0.0188 | 0.2344 |
| <i>NegBV</i> | 0.0233 | 0.0000 | 0.1508 | 0.0000 | 0.0000 |
| <i>VIX</i> | 25.4336 | 21.7340 | 11.6090 | 18.0300 | 27.0400 |
| <i>High VIX</i> | 0.5003 | 1.0000 | 0.5001 | 0.0000 | 1.0000 |
| <i>Crisis</i> | 0.3072 | 0.0000 | 0.4614 | 0.0000 | 1.0000 |
| Observations | 3,740 | | | | |

This table shows univariate summary statistics for *Spread*, *AbsValErr*, *FutVolat*, variables measuring quantitative and qualitative information in earnings conference calls, and control variables. All variables are defined in Table A1.

Table 2: Correlation Table

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) |
|--------------------------|----------|----------|----------|----------|----------|----------|----------|---------|----------|----------|----------|----------|---------|----------|
| (1) <i>Spread</i> | 1.00 | | | | | | | | | | | | | |
| (2) <i>AbsValErr</i> | 0.32*** | 1.00 | | | | | | | | | | | | |
| (3) <i>FutVolat</i> | 0.58*** | 0.46*** | 1.00 | | | | | | | | | | | |
| (4) <i>GoodNews</i> | 0.21*** | 0.08*** | 0.18*** | 1.00 | | | | | | | | | | |
| (5) <i>BadNews</i> | 0.31*** | 0.16*** | 0.35*** | -0.09*** | 1.00 | | | | | | | | | |
| (6) <i>BadNewsInd</i> | 0.17*** | 0.07*** | 0.20*** | -0.25*** | 0.36*** | 1.00 | | | | | | | | |
| (7) <i>Guidance</i> | -0.29*** | -0.10*** | -0.20*** | -0.09*** | -0.14*** | -0.18*** | 1.00 | | | | | | | |
| (8) <i>GuidanceLow</i> | -0.07*** | -0.04** | -0.04** | -0.07*** | -0.03** | 0.03** | 0.37*** | 1.00 | | | | | | |
| (9) <i>FinTerms</i> | 0.12*** | 0.02 | 0.09*** | 0.07*** | 0.14*** | 0.09*** | -0.10*** | -0.04** | 1.00 | | | | | |
| (10) <i>FLS Earnings</i> | -0.09*** | -0.02 | -0.04** | 0.01 | 0.01 | -0.02 | 0.26*** | 0.09*** | 0.34*** | 1.00 | | | | |
| (11) <i>Walkdown</i> | 0.16*** | 0.06*** | 0.16*** | 0.01 | 0.11*** | 0.14*** | -0.10*** | -0.02 | 0.09*** | 0.00 | 1.00 | | | |
| (12) <i>Tone</i> | -0.24*** | -0.14*** | -0.33*** | -0.04** | -0.22*** | -0.24*** | 0.14*** | -0.03* | -0.21*** | -0.06*** | -0.19*** | 1.00 | | |
| (13) <i>Uncertainty</i> | 0.14*** | 0.06*** | 0.21*** | 0.04** | 0.09*** | 0.05*** | -0.04** | 0.00 | 0.06*** | 0.05*** | 0.07*** | -0.36*** | 1.00 | |
| (14) <i>FLS Other</i> | 0.14*** | 0.09*** | 0.17*** | 0.06*** | 0.03* | -0.00 | 0.01 | 0.05*** | -0.04** | 0.18*** | -0.02 | 0.03** | 0.14*** | 1.00 |
| (15) <i>AnalystQs</i> | -0.04** | -0.00 | 0.01 | 0.03 | -0.01 | -0.01 | 0.09*** | 0.05*** | -0.04** | -0.02 | 0.07*** | -0.00 | 0.03* | -0.05*** |

This table shows univariate Pearson correlations between *Spread*, *AbsValErr*, *FutVolat*, and variables measuring quantitative and qualitative information in earnings conference calls. All variables are defined in Table A1. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 3: Analysts' Forecasts of Fundamental Risk Following Earnings Conference Calls.

| | <i>Spread</i> | | |
|--|----------------------|----------------------|----------------------|
| <i>Quantitative Information</i> | | | |
| <i>GoodNews</i> | 2.338** (2.32) | | 2.363** (2.29) |
| <i>BadNews</i> | 3.647*** (4.51) | | 3.573*** (4.40) |
| <i>BadNewsInd</i> | 0.022** (2.43) | | 0.017* (1.89) |
| <i>Guidance</i> | -0.033*** (-3.34) | | -0.032*** (-3.17) |
| <i>GuidanceLow</i> | 0.013 (1.43) | | 0.010 (1.07) |
| <i>FinTerms</i> | -2.480*** (-2.96) | | -2.414*** (-2.87) |
| <i>FLS Earnings</i> | 0.011 (0.02) | | -0.290 (-0.42) |
| <i>Walkdown</i> | 0.033*** (4.89) | | 0.032*** (4.76) |
| <i>Qualitative Information</i> | | | |
| <i>Tone</i> | | -0.036*** (-4.26) | -0.023*** (-2.70) |
| <i>Uncertainty</i> | | 0.018 (0.96) | 0.020 (1.07) |
| <i>FLS Other</i> | | 0.135 (1.19) | 0.151 (1.32) |
| <i>AnalystQs</i> | | -0.002*** (-3.17) | -0.002*** (-3.61) |
| <i>Controls</i> | | | |
| <i>FirmSize</i> | -0.022*** (-4.94) | -0.023*** (-4.97) | -0.023*** (-5.17) |
| <i>BTM</i> | 0.057*** (3.80) | 0.065*** (3.92) | 0.055*** (3.63) |
| <i>NegBV</i> | -0.004 (-0.02) | -0.006 (-0.03) | -0.005 (-0.02) |
| <i>BTM × NegBV</i> | -1.053*** (-2.86) | -1.067*** (-2.90) | -1.059*** (-2.84) |
| <i>Leverage</i> | 0.006*** (3.36) | 0.006*** (3.73) | 0.006*** (3.31) |
| <i>Leverage × NegBV</i> | -0.008 (-0.29) | -0.011 (-0.40) | -0.007 (-0.26) |
| <i>Loss</i> | 0.090*** (4.10) | 0.107*** (4.56) | 0.093*** (4.20) |
| <i>EarnVol</i> | 0.368 (1.45) | 0.404 (1.62) | 0.353 (1.37) |
| <i>Beta</i> | 0.165*** (9.96) | 0.178*** (10.66) | 0.160*** (9.68) |
| <i>IdioRisk</i> | 0.049*** (5.63) | 0.055*** (6.24) | 0.047*** (5.45) |
| <i>BaseReturn</i> | 0.143*** (5.09) | 0.153*** (5.37) | 0.141*** (5.04) |
| <i>Analyst FE</i> | Yes | Yes | Yes |
| <i>Industry FE</i> | Yes | Yes | Yes |
| <i>Year-Quarter FE</i> | Yes | Yes | Yes |
| Observations | 3,740 | 3,740 | 3,740 |
| Adj. R^2 | 0.629 | 0.617 | 0.632 |

This table shows the estimated coefficients from regressing *Spread* on variables measuring quantitative and qualitative information in earnings calls and other controls. Analyst, industry and year-quarter fixed effects, and the constant are included in the regressions, but are not reported. All variables are defined in Table A1. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively, using the two-tailed t-test (t-statistics in parenthesis). Reported statistics are based on standard errors clustered at the firm level.

Table 4: Quantitative and Qualitative Information, Analysts' Forecasts of Fundamental Risk during Periods of High and Low Macroeconomic Uncertainty.

| Panel A: Low and High VIX Periods | | | | | | | |
|--|----------------|--------|-------|-----------------|--------|-------|-------------------|
| | Low VIX | | | High VIX | | | Difference |
| | Mean | Med | STD | Mean | Med | STD | High-Low |
| <i>Spread</i> | 0.632 | 0.571 | 0.270 | 0.726 | 0.666 | 0.312 | 0.094*** |
| <i>AbsValErr</i> | 0.296 | 0.228 | 0.266 | 0.398 | 0.312 | 0.347 | 0.102*** |
| <i>FutVolat</i> | 0.017 | 0.015 | 0.009 | 0.023 | 0.021 | 0.012 | 0.006*** |
| <i>UE</i> | 0.0009 | 0.0006 | 0.008 | 0.0001 | 0.0006 | 0.011 | -0.001** |
| <i>GoodNews</i> | 0.002 | 0.0006 | 0.004 | 0.002 | 0.0007 | 0.005 | 0.0002 |
| <i>BadNews</i> | 0.001 | 0.000 | 0.006 | 0.002 | 0.000 | 0.009 | 0.001*** |
| <i>BadNewsInd</i> | 0.223 | 0.000 | 0.416 | 0.259 | 0.000 | 0.438 | 0.036* |
| <i>Guidance</i> | 0.510 | 1.000 | 0.500 | 0.493 | 0.000 | 0.500 | -0.017 |
| <i>GuidanceLow</i> | 0.131 | 0.000 | 0.336 | 0.117 | 0.000 | 0.322 | -0.014 |
| <i>FinTerms</i> | 0.021 | 0.020 | 0.007 | 0.023 | 0.021 | 0.007 | 0.001*** |
| <i>FLS Earnings</i> | 0.006 | 0.005 | 0.006 | 0.007 | 0.006 | 0.006 | 0.001** |
| <i>Walkdown</i> | 0.364 | 0.000 | 0.481 | 0.444 | 0.000 | 0.497 | 0.080*** |
| <i>Tone</i> | 0.636 | 0.631 | 0.574 | 0.444 | 0.459 | 0.610 | -0.191*** |
| <i>Uncertainty</i> | 0.911 | 0.899 | 0.219 | 0.954 | 0.934 | 0.234 | 0.043*** |
| <i>FLS Other</i> | 0.114 | 0.109 | 0.039 | 0.126 | 0.123 | 0.042 | 0.012*** |
| <i>AnalystQs</i> | 3.873 | 2.571 | 5.013 | 4.236 | 2.667 | 5.821 | 0.363 |
| <i>VIX</i> | 18.17 | 18.03 | 1.954 | 32.70 | 27.04 | 12.67 | 14.78*** |
| <i>Crisis</i> | 0.117 | 0 | 0.322 | 0.496 | 0 | 0.500 | 0.366*** |
| Observations | 1,869 | | | 1,871 | | | |

| Panel B: Crisis and No-Crisis Periods | | | | | | | |
|--|------------------|--------|-------|---------------|--------|-------|-------------------|
| | No-Crisis | | | Crisis | | | Difference |
| | Mean | Med | STD | Mean | Med | STD | Crisis-No-Crisis |
| <i>Spread</i> | 0.647 | 0.588 | 0.274 | 0.751 | 0.682 | 0.330 | 0.104*** |
| <i>AbsValErr</i> | 0.278 | 0.208 | 0.258 | 0.502 | 0.432 | 0.368 | 0.224*** |
| <i>FutVolat</i> | 0.017 | 0.015 | 0.008 | 0.029 | 0.026 | 0.013 | 0.012*** |
| <i>UE</i> | 0.001 | 0.0007 | 0.008 | -0.0009 | 0.0005 | 0.013 | -0.002*** |
| <i>GoodNews</i> | 0.002 | 0.0007 | 0.004 | 0.002 | 0.0005 | 0.005 | -0.0001 |
| <i>BadNews</i> | 0.001 | 0.000 | 0.006 | 0.003 | 0.000 | 0.011 | 0.002*** |
| <i>BadNewsInd</i> | 0.213 | 0.000 | 0.409 | 0.307 | 0.000 | 0.462 | 0.094*** |
| <i>Guidance</i> | 0.512 | 1.000 | 0.499 | 0.479 | 0.000 | 0.499 | -0.033 |
| <i>GuidanceLow</i> | 0.124 | 0.000 | 0.329 | 0.123 | 0.000 | 0.328 | 0.002 |
| <i>FinTerms</i> | 0.022 | 0.021 | 0.007 | 0.023 | 0.022 | 0.008 | 0.001*** |
| <i>FLS Earnings</i> | 0.007 | 0.005 | 0.006 | 0.007 | 0.006 | 0.006 | 0.000 |
| <i>Walkdown</i> | 0.366 | 0.000 | 0.481 | 0.491 | 0.000 | 0.500 | 0.125*** |
| <i>Tone</i> | 0.643 | 0.630 | 0.558 | 0.309 | 0.342 | 0.627 | -0.332*** |
| <i>Uncertainty</i> | 0.915 | 0.905 | 0.220 | 0.969 | 0.951 | 0.236 | 0.054*** |
| <i>FLS Other</i> | 0.118 | 0.113 | 0.041 | 0.125 | 0.122 | 0.042 | 0.007*** |
| <i>AnalystQs</i> | 3.982 | 2.583 | 5.365 | 4.217 | 2.667 | 5.587 | 0.234 |
| <i>VIX</i> | 20.93 | 19.32 | 4.831 | 35.58 | 28.92 | 15.41 | 14.65*** |
| Observations | 2,589 | | | 1,148 | | | |

This table shows univariate summary statistics for *Spread*, *AbsValErr*, and variables measuring quantitative and qualitative information in earnings conference calls for periods of low (first column) and high (second column) macroeconomic uncertainty for (1) low and high VIX periods (*Low VIX*: low market volatility; *High VIX*: high market volatility); (2) no-crisis and crisis periods (*NoCrisis*: low macroeconomic uncertainty; *Crisis*: high macroeconomic uncertainty). Low and high VIX periods are identified relative to the sample median. No crisis and crisis periods are those identified by NBER. All variables are defined in Table A1. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively, using the two-sample t-test and clustering of standard errors at the firm level.

Table 5: Analysts' Forecasts of Fundamental Risk Following Earnings Conference Calls. Periods of Low vs. High Macroeconomic Uncertainty.

| Panel A: Spread in Periods of Low vs. High Market Volatility | | | |
|---|----------------------|----------------------|-------------------------|
| | <i>LowVIX</i> | <i>HighVIX</i> | <i>LowVIX - HighVIX</i> |
| <u>Quantitative Information</u> | | | |
| <i>GoodNews</i> | 2.892** (2.20) | 3.284** (2.13) | -0.392 (-0.04) |
| <i>BadNews</i> | 3.912*** (2.73) | 4.331*** (3.92) | -0.418 (-0.06) |
| <i>BadNewsInd</i> | 0.019 (1.64) | 0.018 (1.20) | 0.001 (0.01) |
| <i>Guidance</i> | -0.037*** (-2.87) | -0.030** (-2.27) | -0.007 (-0.22) |
| <i>GuidanceLow</i> | 0.023* (1.95) | 0.004 (0.23) | 0.019 (1.23) |
| <i>FinTerms</i> | -2.973*** (-3.05) | -0.220 (-0.17) | -2.752+ (-3.46) |
| <i>FLS Earnings</i> | -0.859 (-1.11) | 0.310 (0.28) | -1.169 (-0.91) |
| <i>Walkdown</i> | 0.039*** (4.25) | 0.042*** (4.12) | -0.004 (-0.08) |
| <u>Qualitative Information</u> | | | |
| <i>Tone</i> | -0.022** (-2.22) | -0.064*** (-4.93) | 0.042+++ (8.05) |
| <i>Uncertainty</i> | 0.033 (1.38) | 0.027 (0.98) | 0.007 (0.04) |
| <i>FLS Other</i> | 0.129 (0.88) | 0.293* (1.85) | -0.164 (0.74) |
| <i>AnalystQs</i> | -0.002*** (-2.84) | -0.003*** (-4.25) | 0.001 (0.86) |
| <u>Controls</u> | | | |
| <i>FirmSize</i> | -0.024*** (-4.21) | -0.037*** (-6.84) | 0.013+++ (4.10) |
| <i>BTM</i> | 0.091*** (4.16) | 0.043* (1.85) | 0.048 (2.34) |
| <i>NegBV</i> | 0.259 (0.91) | -0.402*** (-3.20) | 0.661++ (5.73) |
| <i>BTM × NegBV</i> | -0.728* (-1.70) | -1.636*** (-4.73) | 0.908+++ (8.91) |
| <i>Leverage</i> | 0.005*** (3.10) | 0.007*** (2.67) | -0.002 (-0.36) |
| <i>Leverage × NegBV</i> | 0.023 (0.65) | -0.054*** (-3.44) | 0.077++ (4.84) |
| <i>Loss</i> | 0.087*** (3.27) | 0.083*** (2.86) | 0.004 (0.01) |
| <i>Earn Vol</i> | 0.799*** (2.80) | 0.103 (0.29) | 0.696+ (3.33) |
| <i>Beta</i> | 0.133*** (8.02) | 0.135*** (5.36) | -0.002 (-0.01) |
| <i>IdioRisk</i> | 0.019** (2.37) | 0.025** (2.04) | -0.006 (-0.24) |
| <i>BaseReturn</i> | 0.153*** (3.78) | 0.157*** (4.47) | -0.004 (-0.01) |
| <i>Analyst FE, Industry FE</i> | Yes | Yes | |
| Observations | 1,869 | 1,871 | |
| Adj. R^2 | 0.636 | 0.569 | |

This table shows the estimated coefficients from a regression of *Spread* on variables measuring quantitative and qualitative information in earnings conference calls and other controls for periods of low (first column) and high (second column) macroeconomic uncertainty. In Panels A and B, macroeconomic uncertainty is measured with the VIX index and financial *Crisis* indicators, respectively. (Table description continues on the next page...)

Table 5: Analysts' Forecasts of Fundamental Risk Following Earnings Conference Calls. Periods of High Macroeconomic Uncertainty.

| Panel B: Spread in Periods of Financial Crisis | | | |
|---|----------------------|----------------------|---------------------------|
| | <i>No Crisis</i> | <i>Crisis</i> | <i>No Crisis – Crisis</i> |
| Quantitative Information | | | |
| <i>GoodNews</i> | 2.607** (2.10) | 4.341** (2.12) | -1.734 (0.44) |
| <i>BadNews</i> | 4.225*** (2.80) | 3.173*** (2.93) | 1.052 (0.37) |
| <i>BadNewsInd</i> | 0.011 (1.01) | 0.025 (1.33) | -0.014 (-0.44) |
| <i>Guidance</i> | -0.027** (-2.20) | -0.057*** (-2.93) | 0.030 (1.83) |
| <i>GuidanceLow</i> | 0.005 (0.50) | 0.033* (1.78) | -0.028 (-1.97) |
| <i>FinTerms</i> | -2.884*** (-3.35) | -0.069 (-0.04) | -2.815+ (-2.84) |
| <i>FLS Earnings</i> | -1.045 (-1.32) | 0.977 (0.77) | -2.022 (2.20) |
| <i>Walkdown</i> | 0.033*** (4.42) | 0.043*** (3.22) | -0.010 (-0.46) |
| Qualitative Information | | | |
| <i>Tone</i> | -0.023** (-2.24) | -0.059*** (-3.92) | 0.036++ (5.42) |
| <i>Uncertainty</i> | 0.031 (1.31) | 0.055 (1.61) | -0.024 (-0.34) |
| <i>FLS Other</i> | 0.142 (1.15) | 0.563*** (2.64) | -0.421+ (-3.66) |
| <i>AnalystQs</i> | -0.003*** (-4.28) | -0.001 (-1.26) | -0.001 (-1.36) |
| Controls | | | |
| <i>FirmSize</i> | -0.030*** (-5.43) | -0.034*** (-4.99) | 0.004 (0.24) |
| <i>BTM</i> | 0.078*** (4.38) | 0.086*** (2.83) | -0.009 (-0.07) |
| <i>NegBV</i> | 0.123 (0.44) | -0.623*** (-4.09) | 0.746++ (5.67) |
| <i>BTM × NegBV</i> | -1.125*** (-3.28) | -2.204*** (-8.46) | 1.079+++ (11.91) |
| <i>Leverage</i> | 0.005** (2.40) | 0.010*** (3.40) | -0.005 (-2.66) |
| <i>Leverage × NegBV</i> | 0.015 (0.42) | -0.088*** (-2.90) | 0.102++ (5.04) |
| <i>Loss</i> | 0.078*** (3.34) | 0.129*** (2.84) | -0.051 (-1.19) |
| <i>EarnVol</i> | 0.497* (1.88) | 0.119 (0.25) | 0.378 (0.60) |
| <i>Beta</i> | 0.133*** (7.23) | 0.124*** (4.11) | 0.009 (0.07) |
| <i>IdioRisk</i> | 0.025*** (2.97) | 0.002 (0.20) | 0.023+ (3.81) |
| <i>BaseReturn</i> | 0.129*** (2.80) | 0.170*** (6.64) | -0.041 (-0.93) |
| <i>Analyst FE</i> | Yes | Yes | |
| <i>Industry FE</i> | Yes | Yes | |
| Observations | 2,591 | 1,149 | |
| Adj. R^2 | 0.622 | 0.589 | |

Analyst and industry fixed effects, and the constant are included in the regressions, but are not reported. All variables are defined in Table A1. ***, **, * (+++, ++, +) indicate significance at the 1%, 5%, and 10% levels, respectively, using the two-tailed t-test (F-test) (t- (F-) statistics in parenthesis). Reported statistics are based on the clustering of standard errors at the firm level.

Table 6: Mapping of Qualitative and Quantitative Information into Spread, Valuation Errors, and Future Return Volatility.

| Panel A: Full Sample | | | | | |
|---|---------------------------------------|--------------------|----------------------|----------------------|----------------------|
| | Effects on Spread (Mediating Path) | Direct Effects | Indirect Effects | Direct Effects | Indirect Effects |
| | | <i>AbsValErr</i> | | <i>FutVolat</i> | |
| <i>Risk Forecast</i> | | | | | |
| <i>Spread</i> | | 0.168*** (5.77) | | 0.188*** (9.26) | |
| <i>Quantitative Information</i> | | | | | |
| <i>GoodNews</i> | 0.030* (1.71) | 0.020 (0.84) | 0.005 (1.60) | 0.033*** (2.63) | 0.007** (2.22) |
| <i>BadNews</i> | 0.099*** (4.46) | 0.049 (1.61) | 0.017*** (3.45) | 0.117*** (5.98) | 0.019*** (4.03) |
| <i>BadNewsInd</i> | 0.024* (1.87) | -0.020 (-1.23) | 0.004* (1.66) | 0.010 (0.83) | 0.004* (1.93) |
| <i>Guidance</i> | -0.054*** (-3.32) | 0.003 (0.13) | -0.009*** (-2.86) | -0.022 (-1.18) | -0.010*** (-3.08) |
| <i>GuidanceLow</i> | 0.014 (1.45) | -0.024 (-1.50) | 0.002 (1.44) | 0.006 (0.90) | 0.002 (1.08) |
| <i>FinTerms</i> | -0.062*** (-3.03) | -0.028 (-1.15) | -0.010*** (-2.62) | -0.023 (-1.42) | -0.011*** (-2.77) |
| <i>FLS Earnings</i> | -0.005 (-0.39) | 0.006 (0.31) | -0.001 (-0.39) | -0.009 (-0.75) | -0.001 (-0.42) |
| <i>Walkdown</i> | 0.050*** (4.59) | 0.002 (0.12) | 0.008*** (3.52) | 0.013 (1.54) | 0.010*** (4.28) |
| <i>Qualitative Information</i> | | | | | |
| <i>Tone</i> | -0.047*** (-2.75) | -0.031 (-1.53) | -0.008** (-2.46) | -0.083*** (-4.40) | -0.009*** (-2.44) |
| <i>Uncertainty</i> | 0.016 (1.22) | -0.022 (-1.26) | 0.003 (1.21) | 0.015 (1.19) | 0.003 (1.12) |
| <i>FLS Other</i> | 0.021 (1.35) | 0.025 (1.28) | 0.004 (1.30) | 0.011 (0.98) | 0.004 (1.36) |
| <i>AnalystQs</i> | -0.033*** (-3.42) | -0.021 (-1.41) | -0.006*** (-2.87) | -0.020*** (-2.94) | -0.006*** (-3.18) |
| <i>Controls, Analyst FE, Industry FE, Year-Quarter FE – YES</i> | | | | | |
| Observations: 3,740 | | | | | |
| R^2 | | 0.79 | | 0.76 | |

This table shows the standardized coefficients of a path analysis of the relations between variables capturing quantitative and qualitative information in earnings conference calls and analysts' risk forecasts (as measured by *Spread*) and subsequent valuation errors (*AbsValErr*) and idiosyncratic stock return volatility (*FutVolat*). Panel A reports the results for the full sample. Panels B and C report the results for periods of low and high macroeconomic uncertainty, respectively. We use a structural equation model to estimate the direct and indirect effects of quantitative and qualitative variables on *AbsValErr* and *FutVolat*, mediated by *Spread*. All control variables are same as in Table 3. All variables are defined in Table A1. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively, using the Sobel test (Sobel (1987)).

Table 6: Mapping of Qualitative and Quantitative Information into Spread, Valuation Errors, and Future Return Volatility.

| | Effects on Spread (Mediating Path) | Direct Effects | Indirect Effects | Direct Effects | Indirect Effects |
|--|---------------------------------------|----------------------|----------------------|----------------------|----------------------|
| Panel B: Period of Low Macroeconomic Uncertainty. | | | | | |
| | | <i>AbsValErr</i> | | <i>FutVolat</i> | |
| <i>Spread</i> | | 0.092** (2.45) | | 0.142*** (5.19) | |
| Quantitative Information | | | | | |
| <i>GoodNews</i> | 0.042* (1.92) | 0.038 (0.93) | 0.002 (1.09) | 0.026 (1.52) | 0.006* (1.89) |
| <i>BadNews</i> | 0.093** (2.20) | 0.004 (0.12) | 0.008* (1.81) | 0.049*** (3.36) | 0.013* (1.97) |
| <i>BadNewsInd</i> | 0.034* (1.99) | 0.013 (0.60) | 0.003 (1.34) | 0.022** (2.01) | 0.005* (1.74) |
| <i>Guidance</i> | -0.046** (-2.02) | -0.017 (-0.63) | -0.005* (-1.68) | -0.052*** (-3.48) | -0.007* (-1.82) |
| <i>GuidanceLow</i> | 0.015 (1.12) | -0.029 (-1.55) | 0.002 (1.12) | 0.024** (2.57) | 0.002 (1.17) |
| <i>FinTerms</i> | -0.078*** (-3.25) | -0.029 (-0.92) | -0.008* (-1.97) | -0.022 (-1.37) | -0.012*** (-2.84) |
| <i>FLS Earnings</i> | -0.026 (-1.49) | 0.001 (0.03) | -0.002 (-1.04) | -0.007 (-0.61) | -0.003 (-1.26) |
| <i>Walkdown</i> | 0.053*** (3.53) | -0.006 (-0.36) | 0.005** (2.01) | 0.005 (0.62) | 0.008*** (2.97) |
| Qualitative Information | | | | | |
| <i>Tone</i> | -0.036* (-1.68) | 0.014 (0.51) | -0.004* (-1.72) | -0.041*** (-2.87) | -0.006* (-1.74) |
| <i>Uncertainty</i> | 0.027 (1.32) | -0.013 (-0.54) | 0.003 (1.19) | 0.008 (0.65) | 0.004 (1.33) |
| <i>FLS Other</i> | 0.015 (0.77) | -0.002 (-0.07) | 0.002 (1.02) | 0.004 (0.30) | 0.002 (0.91) |
| <i>AnalystQs</i> | -0.022* (-1.85) | -0.002 (-0.12) | -0.003* (-1.69) | -0.019** (-2.35) | -0.003* (-1.91) |
| <i>Controls, Analyst FE, Industry FE – YES</i> | | | | | |
| Observations: 1,671. R^2 for <i>AbsValErr</i> and <i>FutVolat</i> models is 0.75 and 0.80, respectively. | | | | | |
| Panel C: Period of High Macroeconomic Uncertainty. | | | | | |
| | | <i>AbsValErr</i> | | <i>FutVolat</i> | |
| <i>Spread</i> | | 0.175*** (4.24) | | 0.263*** (10.57) | |
| Quantitative Information | | | | | |
| <i>GoodNews</i> | 0.050** (2.09) | 0.004 (0.12) | 0.009* (1.74) | 0.031 (1.37) | 0.015** (2.29) |
| <i>BadNews</i> | 0.125*** (4.44) | 0.072** (2.01) | 0.022*** (2.96) | 0.103*** (5.18) | 0.032*** (3.80) |
| <i>BadNewsInd</i> | 0.022 (1.11) | -0.026 (-1.12) | 0.003 (1.01) | 0.029 (1.29) | 0.005 (1.10) |
| <i>Guidance</i> | -0.061*** (-2.94) | 0.021 (0.58) | -0.011** (-2.36) | -0.005 (-0.18) | -0.017*** (-2.90) |
| <i>GuidanceLow</i> | 0.015 (1.10) | -0.028 (-1.04) | 0.002 (1.08) | -0.010 (-0.82) | 0.003 (0.90) |
| <i>FinTerms</i> | -0.002 (-0.07) | -0.007 (-0.21) | -0.001 (-0.06) | 0.025 (0.97) | 0.004 (0.06) |
| <i>FLS Earnings</i> | 0.002 (0.11) | 0.027 (0.95) | 0.001 (0.11) | -0.004 (-0.21) | 0.001 (0.02) |
| <i>Walkdown</i> | 0.070*** (4.56) | 0.017 (0.75) | 0.012*** (3.23) | 0.025* (1.65) | 0.019*** (4.43) |
| Qualitative Information | | | | | |
| <i>Tone</i> | -0.127*** (-5.31) | -0.109*** (-3.82) | -0.022*** (-3.26) | -0.201*** (-6.93) | -0.033*** (-4.32) |
| <i>Uncertainty</i> | 0.034* (1.81) | -0.029 (-1.22) | 0.006* (1.69) | 0.018 (0.92) | 0.008* (1.65) |
| <i>FLS Other</i> | 0.043** (2.11) | 0.035 (1.32) | 0.008* (1.88) | 0.023 (1.41) | 0.012** (2.17) |
| <i>AnalystQs</i> | -0.052*** (-4.13) | -0.013 (-0.66) | -0.009*** (-2.90) | -0.023* (-1.97) | -0.014*** (-3.84) |
| <i>Controls, Analyst FE, Industry FE – YES</i> | | | | | |
| Observations: 2,069. R^2 for <i>AbsValErr</i> and <i>FutVolat</i> models is 0.69 and 0.68, respectively. | | | | | |

Table 7: Analysts' Forecasts of Fundamental Risk for High and Low Earnings Surprise Terciles by High and Low Tone Terciles.

| <i>Panel A. Averages of Spread and Valuation Error, Sort by Unexpected Earnings</i> | | | | |
|---|-------------------|-------------------|----------------------|----------------------|
| | Low UE | Med UE | High UE | Low-High UE |
| <i>Spread</i> | 0.708 | 0.599 | 0.727 | -0.019 (-1.26) |
| Observations | [1,298] | [1,205] | [1,237] | |
| <i>Panel B. Averages of Spread and Valuation Error - Sort by Tone</i> | | | | |
| | Low Tone | Med Tone | High Tone | Low-High Tone |
| <i>Spread</i> | 0.731 | 0.681 | 0.623 | 0.108*** (6.10) |
| Observations | [1,256] | [1,248] | [1,236] | |
| <i>Panel C. Averages of Spread - Two-way Sort by Unexpected Earnings and Tone</i> | | | | |
| | Low Tone | Med Tone | High Tone | Low-High Tone |
| Low UE | 0.752 [552] | 0.721 [431] | 0.609 [315] | 0.143*** (5.24) |
| Med UE | 0.638 [321] | 0.603 [378] | 0.571 [506] | 0.067*** (3.10) |
| High UE | 0.780 [383] | 0.709 [439] | 0.698 [415] | 0.082*** (2.92) |
| Low-High UE | -0.027 (-1.09) | -0.011 (-0.51) | -0.088*** (-3.73) | |

This table shows the average *Spread* for (1) low, medium and high earnings surprise terciles (*Low UE*: bad news; *High UE*: good news); (2) high, medium, and low tone terciles (*Low Tone*: pessimistic earnings call; *High Tone*: optimistic earnings call). Earnings surprise and tone terciles are created using quarterly independent double sorts of quarterly earnings conference calls by the corresponding unexpected earnings (*UE*) and tone of the conference call (*Tone*). *Tone* and *UE* are defined in Table A1. T-statistics based on clustering at the firm level (number of observations) are in parenthesis (squared brackets).

Table 8: Analysts' Forecasts of Fundamental Risk and Contradictory Signals in Unexpected Earnings and Tone in Earnings Conference Calls.

| | Low UE | High UE |
|------------------------|----------------------|---------------------|
| <i>High Tone</i> | -0.026** (-2.37) | 0.006 (0.45) |
| <i>Low Tone</i> | 0.004 (0.29) | 0.032*** (2.68) |
| <i>Tonal Ambiguity</i> | 0.033** (2.44) | 0.013 (0.91) |
| <i>AbsUE</i> | 5.390*** (5.70) | 1.399 (0.85) |
| <i>Guidance</i> | -0.040*** (-3.07) | -0.026** (-2.04) |
| <i>GuidanceLow</i> | 0.009 (0.83) | 0.005 (0.34) |
| <i>FinTerms</i> | -3.482*** (-3.08) | -1.153 (-1.06) |
| <i>FLS Earnings</i> | 0.938 (1.01) | -1.430 (-1.44) |
| <i>Walkdown</i> | 0.033*** (3.48) | 0.036*** (3.74) |
| <i>Uncertainty</i> | 0.021 (0.84) | 0.038* (1.70) |
| <i>FLS Other</i> | 0.022 (0.14) | 0.197 (1.36) |
| <i>AnalystQs</i> | -0.003*** (-4.11) | -0.001 (-1.62) |
| <i>Controls</i> | Yes | Yes |
| <i>Analyst FE</i> | Yes | Yes |
| <i>Industry FE</i> | Yes | Yes |
| <i>Year-Quarter FE</i> | Yes | Yes |
| Observations | 1,870 | 1,870 |
| Adj. R^2 | 0.667 | 0.603 |

This table shows the estimated coefficients from regressing *Spread* on variables measuring quantitative and qualitative information in earnings conference calls and other controls for firms with *Low* and *High* unexpected earnings (UE) relative to the sample median. Analyst, industry and year-quarter fixed effects, and the constant are included in the regressions, but are not reported. All variables are defined in Table A1. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively, using the two-tailed t-test (t-statistics in parenthesis). Reported statistics are based on the clustering of standard errors at the firm level.

Table 9: Analysts' Forecasts of Fundamental Risk and Revenue vs. Expense Surprise in Earnings Conference Calls.

| | <i>Spread</i> | |
|-------------------------------|---------------|-----------|
| | | |
| <i>Good News Revenues</i> | 0.182* | 0.203* |
| | (1.69) | (1.92) |
| <i>Bad News Revenues</i> | 1.388** | 1.335** |
| | (2.06) | (2.09) |
| <i>Bad News Revenues Ind</i> | 0.008 | 0.005 |
| | (0.66) | (0.44) |
| <i>Good News Expenses</i> | -0.612 | -0.585 |
| | (-0.95) | (-0.96) |
| <i>Bad News Expenses</i> | -0.115 | -0.139 |
| | (-1.26) | (-1.61) |
| <i>Good News Expenses Ind</i> | 0.006 | 0.007 |
| | (0.54) | (0.62) |
| <i>Guidance</i> | -0.026** | -0.023** |
| | (-2.43) | (-2.16) |
| <i>GuidanceLow</i> | 0.005 | -0.001 |
| | (0.47) | (-0.06) |
| <i>FinTerms</i> | -3.151*** | -3.031*** |
| | (-3.17) | (-3.04) |
| <i>FLS Earnings</i> | 0.573 | 0.322 |
| | (0.75) | (0.40) |
| <i>Walkdown</i> | 0.039*** | 0.034*** |
| | (4.85) | (4.22) |
| <i>Tone</i> | | -0.033*** |
| | | (-3.41) |
| <i>Uncertainty</i> | | 0.008 |
| | | (0.39) |
| <i>FLS Other</i> | | 0.114 |
| | | (0.84) |
| <i>AnalystQs</i> | | -0.001* |
| | | (-1.81) |
| <i>Controls</i> | Yes | Yes |
| <i>Analyst FE</i> | Yes | Yes |
| <i>Industry FE</i> | Yes | Yes |
| <i>Year-Quarter FE</i> | Yes | Yes |
| Observations | 2,747 | 2,747 |
| Adj. R^2 | 0.621 | 0.624 |

This table shows the estimated coefficients from regressing *Spread* on *Revenue* vs. *Expense* surprise and other variables measuring quantitative and qualitative information in earnings conference calls and firm characteristics. Revenue surprise is calculated relative to the revenue consensus forecast issued in the last 60 days prior to the earnings announcement. Expense surprise is the difference between revenue surprise and earnings surprise. The split of revenue and expense surprises into good vs. bad news is performed analogously to the earnings surprise in Table 3. to Analyst, industry and year-quarter fixed effects, and the constant are included in the regressions, but are not reported. All variables are defined in Table A1. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively, using the two-tailed t-test (t-statistics in parenthesis). Reported statistics are based on the clustering of standard errors at the firm level.

Table 10: Price Target Dispersion and Range Following Earnings Announcements.

| | Price Target Dispersion | Price Target Range |
|--|-------------------------|----------------------|
| <i>Quantitative Information</i> | | |
| <i>GoodNews</i> | 1.585* (1.80) | 3.065* (1.87) |
| <i>BadNews</i> | 1.147** (2.13) | 2.180** (2.11) |
| <i>BadNewsInd</i> | 0.009** (2.19) | 0.030*** (3.18) |
| <i>Guidance</i> | -0.013*** (-3.11) | -0.023** (-2.23) |
| <i>GuidanceLow</i> | 0.004 (1.12) | 0.004 (0.37) |
| <i>FinTerms</i> | -0.645** (-2.11) | -1.270* (-1.74) |
| <i>FLS Earnings</i> | 0.119 (0.39) | 0.146 (0.19) |
| <i>Walkdown</i> | 0.005* (1.74) | 0.013* (1.73) |
| <i>Qualitative Information</i> | | |
| <i>Tone</i> | -0.013*** (-4.25) | -0.035*** (-4.01) |
| <i>Uncertainty</i> | -0.005 (-0.69) | 0.006 (0.30) |
| <i>FLS Other</i> | 0.140*** (3.11) | 0.340*** (3.05) |
| <i>AnalystQs</i> | -0.002* (-1.84) | -0.002** (-2.56) |
| <i>Controls</i> | Yes | Yes |
| <i>Industry FE</i> | Yes | Yes |
| <i>Year-Quarter FE</i> | Yes | Yes |
| Observations | 3,419 | 3,419 |
| Adj. R^2 | 0.317 | 0.442 |

This table shows the estimated coefficients from regressing *Price Target Dispersion* and *Price Target Range* on variables measuring quantitative and qualitative information in earnings conference calls and various firm characteristics. Analyst, industry and year-quarter fixed effects, and the constant are included in the regressions, but are not reported. *Price Target Dispersion* is the standard deviation of one-year-ahead price target forecasts issued by analysts within 10-days after the earnings announcement, scaled by the average value of such forecasts. *Price Target Range* is the difference between the maximum and minimum one-year-ahead price target forecast issued by analysts within 10-days after the earnings announcement, scaled by the average value of such forecasts. All variables are defined in Table A1. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively, using the two-tailed t-test (t-statistics in parenthesis). Reported statistics are based on the clustering of standard errors at the firm level.

Table 11: Analysts' Forecasts of Fundamental Risk Conditional on Past Fundamental Risk.

| | <i>Full Sample</i> | <i>Low Macro Uncertainty</i> | <i>High Macro Uncertainty</i> |
|--|----------------------|------------------------------|-------------------------------|
| <i>LagSpread</i> | 0.740*** (39.42) | 0.824*** (42.33) | 0.717*** (25.86) |
| <i>Quantitative Information</i> | | | |
| <i>GoodNews</i> | -0.033 (-0.04) | 0.927 (1.21) | -0.870 (-0.70) |
| <i>BadNews</i> | 1.466*** (3.15) | 2.095* (1.93) | 1.502*** (2.64) |
| <i>BadNewsInd</i> | 0.005 (0.90) | 0.009 (1.35) | 0.002 (0.22) |
| <i>Guidance</i> | -0.010** (-2.01) | -0.009 (-1.56) | -0.014* (-1.84) |
| <i>GuidanceLow</i> | 0.012** (1.99) | 0.012* (1.88) | 0.021** (2.06) |
| <i>FinTerms</i> | -1.080*** (-2.70) | -1.001** (-2.27) | -0.365 (-0.56) |
| <i>FLS Earnings</i> | -0.578 (-1.54) | -0.304 (-0.63) | -0.814 (-1.35) |
| <i>Walkdown</i> | 0.014*** (3.38) | 0.012** (2.32) | 0.023*** (3.22) |
| <i>Qualitative Information</i> | | | |
| <i>Tone</i> | -0.007* (-1.67) | -0.006 (-1.11) | -0.020*** (-3.31) |
| <i>Uncertainty</i> | 0.014 (1.41) | 0.004 (0.26) | 0.026* (1.79) |
| <i>FLS Other</i> | 0.007 (0.11) | -0.075 (-0.94) | 0.047 (0.56) |
| <i>AnalystQs</i> | -0.000 (-0.25) | -0.000 (-0.95) | -0.000 (-0.05) |
| <i>Controls</i> | Yes | Yes | Yes |
| <i>Analyst FE</i> | Yes | Yes | Yes |
| <i>Industry FE</i> | Yes | Yes | Yes |
| <i>Year-Quarter FE</i> | Yes | No | No |
| Observations | 3,663 | 1,625 | 2,038 |
| Adj. R^2 | 0.845 | 0.890 | 0.808 |

This table shows the estimated coefficients from regressing *Spread* on lagged *Spread* (*LagSpread*), variables measuring quantitative and qualitative information in earnings conference calls and other controls. Column (1) reports coefficient estimates for the full sample, while Columns (2) and (3) report coefficient estimates in periods of low and high macroeconomic uncertainty (as indicated by *Crisis* or *High VIX* (relative to the sample median)), respectively. Analyst and industry fixed effects, and the constant are included in each regressions, but are not reported. Year-quarter fixed effects are included in Column (1). *LagSpread* is the value of *Spread* at the time of the previous analyst report. All other variables are defined in Table A1. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively, using the two-tailed t-test (t-statistics in parenthesis). Reported statistics are based on the clustering of standard errors at the firm level.