Looking under the hood: Quantitative vs qualitative inputs to analyst forecasts of fundamental risk

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Abstract

We study how sell-side analysts map both quantitative and qualitative information from earnings conference calls into their forecasts of fundamental firm risk. We find that analysts perceive firm risk to be lower when absolute earnings surprises are small and tone of the earnings conference calls is more positive. Further, we find that the relative importance of qualitative information increases during periods of high macro-uncertainty (i.e., during NBER crises or periods of high VIX), and this increase improves the calibration of the risk forecasts. While our main results rely on a general measure of *Tone* of language to gauge the qualitative information component of the earnings conference call, additional analyses find that both positive and negative language affects risk forecasts and that extreme language rather than moderate language results in differential risk perceptions. Our results are robust to alternative empirical specifications and increase our understanding of the "black box" that is the analyst forecasting process.

Keywords: analysts' risk forecasts, unexpected earnings, tone, macroeconomic uncertainty.

March 5, 2017

Early Draft. Please do not cite without authors' permission.

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We would like to thank participants of the INSEAD brownbag for their helpful comments and suggestions.

1 Introduction

Decision making in financial markets relies crucially on information. This information flows into markets in different forms and the finance and accounting literature has focused on how capital market participants assess and process information available to them in different guises. Since decisions in capital markets often involve (forecasts of) financial variables, a long literature has predominantly studied the role of information arriving in quantitative form. However, as Tetlock et al. (2008) point out, for both theoretical and empirical reasons quantitative information alone cannot fully explain the behavior of capital markets.[1] As a result, research has focused on how information arriving in qualitative form affects capital market decision making (see Li (2010b) and Loughran and McDonald (2016) for review). Broadly speaking, these studies document an incremental role for qualitative information as inputs to financial decisions: investors respond to qualitative information via stock returns and analysts react via earnings forecast revisions and/or changes in recommendations.[2]

In this paper, we expand this literature on the complementary role of quantitative and qualitative information in capital markets by asking two questions related to the forecasting process of sell-side analysts. First, we ask whether quantitative and qualitative information (jointly) matter for analyst forecasts of firm fundamental *risk*. Given the importance of risk assessment for investment decisions and the role of analysts as primary information intermediaries in capital markets, Zmijewski (1993) issued an early call for research into analysts' ability to assess firm risk. However, decades on, the literature on fundamental risk forecasting is still relatively scarce and to our knowledge there is no empirical evidence on the role of qualitative information in this context.[3]

Second, we ask how conditions of increased macro-uncertainty influence the relative roles of quantitative vs qualitative information for the analysts' process of risk forecasting. Our focus on this question stems from recent research showing that conditions of increased macro-uncertainty both lead to a heightened investor reliance on analyst advice and a change in the properties of analyst output (e.g., Amiram et al. (2014), Loh and Stulz (2016)). Loh and Stulz (2016) in

[1]Tetlock et al. (2008) refer to examples as early as Shiller (1981), Roll (1988), Cutler et al. (1989) to illustrate the awareness that information other than quantitative factors drives stock prices.

[2]See for example Tetlock (2007), Tetlock et al. (2008), Mayew and Venkatachalam (2012), Garcia (2013), Huang et al. (2014),Bochkay et al. (2017), among others.

[3] Lui et al. (2007, 2012) and Joos et al. (2016) are examples of papers that examine analyst forecasts of firm risk using traditional quantitative variables.

particular conclude that analysts "change what they do" when macro-uncertainty increases by working harder (e.g., they issue more frequent earnings revisions or write longer reports). In the same vein, Joos et al. (2016) [JPS] document how the financial crisis of 2008-2009 affects the relative weights of quantitative (market-wide) determinants of analyst forecasts of fundamental firm risk and improves their calibration. However, this research does not answer the question whether analysts change how they process different types of firm-level information (quantitative vs qualitative) under conditions of increased macro-uncertainty. Immediately relevant to this question is the work by Garcia (2013) who documents how conditions of macro-uncertainty during recessions mark an increased role for *sentiment*, a qualitative variable, as a predictor of stock returns. The analysis in Garcia (2013) builds on findings from the psychology and behavioral economics literature to show how aggregate sentiment affect decision making and information processing under different macro-economic circumstances.[4] Therefore, by asking our second question, we build on these findings to deepen our understanding of how different types of information affect analyst forecasts of fundamental firm risk, at a time these forecasts likely increase in importance.

To address our questions, we merge two datasets to construct a unique research setting. The first dataset consists of investment reports that contain scenario-based valuation forecasts issued by Morgan Stanley analysts over the period 2007 through 2012 (see JPS (2016)). We merge this dataset with a comprehensive sample of earnings conference calls used in Bochkay et al. (2017) [BCH] spanning the period 2006 through 2013. While analysts collect information relevant to their risk forecasts from various sources (both private and public), their active participation in earnings conference calls and increased number of follow-up forecast revisions suggest that analysts seem to find information in conference calls useful. Indeed, 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), Table 1). Not only are earnings conference calls a major form of communication firms use to supplement their regulatory filings, they also have the important added benefit that they present market participants with both quantitative and qualitative information about the firm's performance and financial position. The resulting dataset consists of 4,336 observations.

[4]Different from the approach in Garcia (2013), Kacperczyk et al. (2016) develop a rational expectations model that emphasizes the role of the business cycle for the attention allocation by a different set of economic agents in capital markets, namely mutual fund managers. Their model uses the state of the business cycle, i.e., recession vs boom, to predict these managers' changing reliance on different information choices.

Our setting allows exploiting the distinctive features of each of the constituting datasets to address our research questions. In particular, each observation contains the individual analyst's most likely valuation for the firm (i.e., base-case valuation or target price) and a forecasted distribution (or range) of scenario-based valuations (base case plus upside/downside valuations). Intuitively, the wider the distribution modeled by the analyst, the greater the analyst's perception of the uncertainty about state-contingent risk surrounding value of the firm. We therefore use the scenario-based valuations in the reports to define *Spread*, i.e., the width of the valuation range or the difference between a report's upside and downside valuation forecasts, as our measure of analysts' valuation risk forecasts.[5]

Similarly, for each observation, we construct measures of quantitative and qualitative information relating to the earnings conference call. We follow the extant literature and obtain a metric of quantitative information by initially measuring *unexpected earnings* (UE) based on the deviation of actual earnings per share from analyst recent consensus forecast of earnings per share.[6] Since our forecast attribute of interest is fundamental risk we use the absolute value of UE as our main variable of interest ($AbsUE$): larger values of $AbsUE$ indicate larger deviations or 'shocks' to expectations, regardless of their sign. We obtain our metric of qualitative information by measuring the extent to which the earnings conference call projects optimistic or pessimistic views regarding the company's performance and prospects. Specifically, following prior literature on qualitative disclosures (Tetlock (2007), Tetlock et al. (2008), Li (2010a), and Loughran and McDonald (2011)), we construct the variable *Tone* as the number of positive words minus the number of negative from Loughran and McDonald (2011)'s financial sentiment dictionary that occur in the conference call, divided by the total number of words in the conference call.

We expect that if $AbsUE$ and *Tone* capture complementary aspects of future fundamental risk, then both variables will exhibit a relation with our metric of fundamental risk, *Spread*. In terms of the relation of *Spread* and $AbsUE$, we predict that larger deviations from expected earnings (i.e., larger $AbsUE$) will map into larger forecasts of future fundamental risk. To formulate a prediction on the relation between *Spread* and *Tone*, we rely on the work of Kothari et al. (2009). These authors predict and find that disclosures with a positive (negative) tone decrease (increase) firm's

[5]We normalize our measure of *Spread* as a percentage of the midpoint of the analyst's valuation range.
[6]See Table A1 for all variable definitions and data sources.

risk as measured by the cost of capital, stock return volatility, and analyst dispersion.[7] The evidence on the directional link in Kothari et al. (2009) leads us to predict that the relation between *Tone* and *Spread* will be *negative*.

Our first set of analyses provide evidence consistent with our predictions by showing that *Spread* exhibits a non-linear U-shaped relation with unexpected earnings - both large positive and negative unexpected earnings result in higher *Spread*. At the same time, *Spread* is negatively correlated with *Tone*. In other words, analysts map larger shocks to expectations of either sign (*AbsUE*) into increased estimates of future riskiness of the firms, while a more positive *Tone* in earnings conference calls reduces the analysts' perception of the firm's fundamental riskiness. Our result extends the findings in Kothari et al. (2009), Campbell et al. (2014) and Campbell et al. (2017) by documenting a connection between disclosure *Tone* and analysts' perception of risk.[8] Subsequent analyses that regress *Spread* on both variables, with controls for relevant firm and market characteristics, find positive coefficients on *AbsUE* and negative coefficients on *Tone* consistent with the descriptive findings. Overall, these results suggest that analysts jointly consider quantitative and qualitative information from earnings conference calls in their estimates of future fundamental risk.

Having established a correspondence between both types of information in earnings conference calls and analyst fundamental risk forecasts, we next explore whether conditions of macro-uncertainty affect this mapping. We define two variables to capture circumstances of high macroeconomic uncertainty in our sample. One variable identifies sample observations made during periods with elevated values of the VIX index (*High VIX*), while the second variable marks recession periods as defined by the National Bureau of Economic Research (NBER) (*Crisis*).[9] When we augment our base regression to interact macro-uncertainty variables with our previously defined information variables, the coefficients on both interactions with *AbsUE* are insignificant. In contrast, the coefficients on the interactions with *Tone* are negative and highly significant, suggesting that increased

[7] Kothari et al. (2009) derive their prediction based on the work by Ng et al. (2009) who establish a link between disclosure content and the firm's cost of capital within a framework of information asymmetry between the firm's managers and the investment community. Recent work by Campbell et al. (2014) and Campbell et al. (2017) adopts the same framework and, similarly, finds evidence of a directional relation between disclosure *tone* and investors' assessments of risk.

[8] Our finding of a directional link between *Tone* and risk is also consistent with the positive relation between media pessimism and market (Dow Jones) volatility in Tetlock (2007) and the positive relation between 10-K's negativity and stock return volatility in Loughran and McDonald (2011).

[9] While both variables are correlated, they are also distinct because high macro-uncertainty can occur both in up and down markets, whereas recession periods indicate down markets only (Amiram et al., 2014).

levels of macro-uncertainty exacerbate the mapping of qualitative information into the fundamental risk forecasts.

Taken together, our results extend the evidence in JPS (2016) that analysts direct specific effort to their calibration of *ex ante* forecasts of risk, i.e., *Spread*, under conditions of increased macro-uncertainty. To complement these findings, we next address the question of whether the inclusion of quantitative and qualitative information in *Spread* results in better forecasts of fundamental firm risk. We answer this question by studying the relation between *Spread* and *ex post* absolute valuation errors (*AbsValErr*), conditional on the mapping of earnings call information into *Spread* documented above. Intuitively, if analysts correctly assess state-contingent valuation risk, then *Spread* will be associated with the magnitude of *ex post* absolute valuation errors. In other words, *Spread* will relate positively to *AbsValErr* (see JPS (2016)). We use path analysis to model the sequential nature of our variables of interest: earnings surprise and tone of the conference call are followed by analysts' assessments of fundamental firm risk which are then followed by stock return realizations. In other words, we examine the relation between *AbsUE* and *Tone* and absolute valuation errors, with a mediating role for *Spread*. The results of this analysis first confirm the positive relation between *Spread* and absolute valuation errors. Next, we find that the absolute earnings surprise (*AbsUE*) has both direct and indirect effects on *AbsValErr*, while tone of the conference call has an indirect effect on *AbsValErr* mediated through *Spread*. When we take into account different conditions of macro-uncertainty, the results show that *both* quantitative and qualitative information contribute to the improvement in calibration of *Spread* when macro-uncertainty increases. Importantly, we find that increased macro-uncertainty particularly enhances the role of qualitative information in the forecasting setting (both via direct effects on the absolute valuation error and indirect effects mediated through *Spread*). One implication of this finding seems to be that the increased incorporation of qualitative information from the earnings conference call improves the calibration of *Spread* as a forecast metric.

To verify the robustness of our main results and to further deepen our understanding of how *Tone* maps into analyst forecasts of fundamental risk, we carry out additional tests that refine our definition of *Tone* along different dimensions. A first analysis decomposes *Tone* into its positive and negative components and expands our regression specification to include measures of positive and negative tone separately. We find that both variables map into forecasts of risk in a manner consistent with our earlier findings: positive words in earnings calls reduce, while negative words widen *Spread*. In other words, our results do not follow from the netting of word counts, a concern expressed in Loughran and McDonald (2016). Importantly, the finding also shows a symmetric effect of positive and negative tone, complementing previous research that often emphasizes the importance of negative tone only (e.g., Loughran and McDonald (2016)).

Second, we expand the definition of *Tone* to capture the *intensity* of the language used in the earnings conference call. We follow BCH (2017) and examine the use of extreme and moderate language in earnings calls and its mapping into analysts' assessment of future firm risk. We find that the intensity of tone matters: the metric that captures extreme tone of language (e.g., very good, top quality, terrible, failure, etc.) maps into analysts' forecasts of fundamental risk, whereas the metric that captures more moderate tone does not. This result is consistent with findings in the psychology literature that information presented in more extreme way can be more persuasive and impact judgments more strongly (Nisbett and Ross (1980), Hosman (2002)). Relatedly, Hales et al. (2011) and BCH (2017) find that vivid and extreme language significantly influences investors' response to fundamental information. Overall, our result here suggests that moderate tone lacks the *conviction* to influence risk forecasts, while extreme tone carries sufficient persuasion to affect analysts' perception of future firm risk.

Further, our variable *Tone* captures only the overall tone of the earnings conference call and as such does not distinguish between statements in different parts of the earnings conference call. Survey evidence shows though that analysts distinguish between the presentation (i.e., the prepared remarks) and the questions-and-answers (Q&A) parts of the earnings conference call in their forecast generating process (e.g., Brown et al. (2015)). We therefore split the content of each earnings call into these two parts and calculate the *Tone* measures separately for each section. We also explore if the tone of managers or analysts or both in the Q&A session matters for future risk assessments. Our findings show that *Tone* of both sections of the earnings call results in lower *Spread*. In addition, we find that tone of both analyst questions and comments as well as tone of management responses are associated with *Spread* in a similar way. When modeling future firm risk, analysts therefore not only gauge the tone of management but also, and in equal strength, the tone of their peers as they discuss the firm's results. Importantly, the evidence that the tone of the prepared remarks, when only management speaks, affects the forecasts of firm risk alleviates a potential concern that reverse causality drives our relation between *Tone* and *Spread*. Taken together, these additional analyses verify and extend our main results that more positive tone maps into lower forecasts of *Spread*. These refinements highlight the importance of components and intensity of tone, sections of the earnings conference calls, and participants on the call.

Our paper makes the following contributions to the literature. First, we contribute to the literature on the role of different types of information for analyst forecasts. To our knowledge, we are the first to show that tone of earnings conference calls (a metric of qualitative information) relates to analyst forecasts of fundamental risk. Risk forecasts are an important ingredient of the investment decision, but research on forecasts of risk has been relatively scarce because of data requirements. In our novel research setting, we find that qualitative information exhibits a directional relation with estimates of risk, complementing the relation between risk estimates and quantitative metrics of earnings expectation shocks. Second, we contribute to the literature on the effect of macro-uncertainty on how capital market participants process information for their decision making. Our findings are consistent with analysts relying more on qualitative information when forecasting firm fundamental risk in periods of increased macro-uncertainty, at a time when these forecasts likely matter more and quantitative inputs are less precise. We also provide initial evidence that this increased reliance on qualitative information contributes to the improved calibration of the risk forecasts under those circumstances.[10]

In sum, our findings enhance our understanding of how one important category of capital market participants, sell-side analysts, handles information arriving in different forms under potentially changing market circumstances to form expectations about firm fundamentals. As such, we contribute to the research efforts to open up the "black-box" of sell-side financial analyst forecast activities, as suggested by Ramnath et al. (2008), Bradshaw (2011), Brown et al. (2015), and Kothari et al. (2016).

[10] Our findings also complement previous research that shows how increased macro-uncertainty results in an asymmetric response to good or bad information (Williams, 2014).

2 Background and motivation

2.1 Prior research and motivation

2.1.1 Analysts' "black box"

Sell-side analysts are important information intermediaries who help to bridge the information gap between companies and investors (Womack (1996); Jegadeesh et al. (2004); Ramnath et al. (2008); Bradshaw et al. (2016), among others). The major role of an analyst is to accumulate, process, and summarize value-relevant information, so that investors make more informed and timely decisions. Numerous studies in the literature examine properties of analysts' earnings forecasts (e.g., accuracy and dispersion) and their information value to the investment community. While understanding consequences of analysts' forecasts is important, recent studies encourage future research to focus more on how analysts come up with their forecasts and recommendations. For example, in recent literature review on analysts' forecasts, Kothari et al. (2016) conclude that "understanding how analysts form and revise their true expectations is crucial." In a similar vein, Ramnath et al. (2008), Bradshaw (2011), and Brown et al. (2015) emphasize the importance of opening the "black box" of analysts' advice - *what* information analysts use and *how* they use it.

We zoom in on the analysts' "black box" by studying the role of both quantitative financial (e.g., earnings surprise) and qualitative textual (e.g., tone of communication) information in earnings conference calls for analysts' forecast generating process. While joint consideration of both types of information has become prevalent since the early work by Tetlock (2007), we construct a unique research setting to examine unexplored issues in this context. First, unlike prior studies that focus almost exclusively on earnings forecasts, we examine analysts' forecasts of future risk and valuation uncertainty. We focus on risk forecasts for two reasons. First, we build on JPS (2016) who, using a similar sample of scenario-based investment reports, document that the analysts writing these reports exhibit bias in their estimates of expected returns (i.e., their forecasted target price) but not in their estimates of state-contingent valuation risk. Therefore, our focus on risk forecasts likely reduces the effect that analyst forecast bias could have on our conclusions on the relative role of information sources for the forecasts. Second, as mentioned, evidence on the properties of analyst forecasts of risk is scarce, despite a more pronounced recent attention to investor risk perception in the literature (e.g., Li (2006); Kothari et al. (2009); Kravet and Muslu (2013); Hope et al. (2016)).

Second, to better understand analysts' modeling process (i.e., the "black box") following major firm events, we focus on those analyst reports that come out immediately after quarterly earnings announcements accompanied by earnings conference calls. Our focus on earnings announcements together with earnings conference calls builds on a long literature that generally documents the information role of these corporate events (Frankel et al. (1999); Kimbrough (2005); Matsumoto et al. (2011); Mayew and Venkatachalam (2012), Huang et al. (2017)). Specifically, we exploit the setting of 4,336 earnings announcements and conference calls with follow-up analyst reports to define metrics of both quantitative and qualitative information relevant to analyst forecasts of future valuation risk and uncertainty. Intuitively, quantitative financial information such as earnings surprise reflects how a firm performed relative to prior expectations, whereas discussion in earnings conference calls supplements financial numbers with managers' view about firm performance and prospects. Moreover, analysts' active participation in earnings conference calls suggests that they find such corporate events informative (Matsumoto et al. (2011)). Indeed, Brown et al. (2015) survey sell-side analysts to understand which information is the most relevant in their forecast decisions. Earnings conference calls are listed as the third most relevant component of analysts' forecasts after analysts' own industry expertise and their private communications with management (see survey responses in Table 1 of Brown et al. (2015)).

2.1.2 Macro-uncertainty, analyst activities, and quantitative vs qualitative inputs to forecasts

One important feature of our research design is that we explore the role of macro-uncertainty in the forecast setting of fundamental risk. The financial crisis of 2008 prompted a lot of attention on the specific role of analysts and the properties of their output during the so-called bad times, i.e., crisis or states of the economy marked by increased macro-uncertainty. In a research setting similar to ours, JPS (2016) show that following the financial crisis analysts changed the relative magnitude of *Spread*, recalibrated the relation of *Spread* with known risk metrics and improved the predictive properties of the *Spread*. Analysts therefore appear to direct specific effort to their calibration of forecasts of risk in situations of heightened macro-uncertainty. Other recent papers more broadly study the role of analysts as a function of the state of the economy and in particular increased macro-uncertainty. Loh and Stulz (2016) show results consistent with analysts working harder and producing better forecasts during periods of increased uncertainty.[11]

While recent research highlights the relevance of increased macro-uncertainty for the properties of analyst forecasts and analysts' efforts in calibrating their forecasts of risk, it does not answer the question whether the increased macro-uncertainty affects the relative role of quantitative and qualitative information as inputs to fundamental risk forecasts. Speaking to this issue is the work by Garcia (2013). He develops a behavioral argument to predict that conditions of macro-uncertainty during recessions will lead to an increased role for *sentiment* as a predictor of stock returns. Essentially his paper extends the earlier findings in Tetlock (2007) by "showing how the predictability he uncovers is much stronger during economic downturns."(Garcia (2013, p. 1271)). The argument in Garcia (2013), building on evidence from the psychology and behavioral economics literature, is that increased macro-uncertainty creates a setting where individuals will alter their decision-making process by becoming more *sensitive* to news. As a result, sentiment becomes a stronger predictor of returns.[12] If the same behavioral mechanism holds in our context, this would imply that under conditions of increased macro-uncertainty, analysts would ascribe a more important role to qualitative information from earnings conference calls when predicting future fundamental firm risk.

2.2 Morgan Stanley framework

The data used in our study are drawn from scenario-based valuation estimates made by Morgan Stanley analysts in their investments reports. Established in 2007, Morgan Stanley's risk-reward framework requires analysts to expand their analyses to present both upside and downside valuation scenarios, called bull and bear cases, in addition to base-case expectations for the company's stock price, over the following 12 months (see Weyns et al. (2007) and Srinivasan and Lane (2011)

[11]See for example Hope and Kang (2005), Arand and Kerl (2012), Amiram et al. (2014) and Loh and Stulz (2016). All these papers show that traditional metrics of analyst forecast accuracy worsen during times of high uncertainty. However, Loh and Stulz (2016) emphasize the need to scale forecasts differently when gauging the performance of analyst forecasts in crisis times to reflect the increased level of uncertainty in the market.

[12]Other papers follow a different approach to address the question of how changing conditions through the business cycle (i.e., recession vs boom) affect how economic agents process information. Kacperczyk et al. (2016) develop a rational expectations model that explains how the cognitive ability of fund managers to focus on different information sources across the distinct phases of the business cycle determines their skill and performance. In a related paper, Kacperczyk et al. (2014) provide empirical evidence that fund managers that outperform other funds and passive benchmarks do so by becoming stock pickers during expansions and market timers during recessions.

for details).[13] Figure A1 shows an example of the scenario-based valuation estimates created under the risk-return framework at Morgan Stanley. By presenting three valuation forecasts in each investment report, the analyst therefore shows not only the most likely valuation outcome for the firm (the expected target price return), but also a range of plausible outcomes over the forecast horizon (the expect spread of valuation outcomes). The analyst can present his/her conviction on the firm's outlook by either tightening the range between the upside and downside cases, or by skewing the base case/target price towards the upside or downside case scenario they considered more likely (Weyns et al., 2007). Importantly, as of 2007 Morgan Stanley mandated this probabilistic state-contingent view of equity values in investment notes, thus creating a standardized platform for its analysts to formally integrate fundamental risk into their analysis activities and to convey this state-contingent information to their clients.

2.3 Earnings conference call setting

We use earnings announcements accompanied by earnings conference calls as our source of firm-specific quantitative (hard) and qualitative (soft) information relevant to analysts' assessment of future risk and valuation uncertainty. Earnings conference calls are one of the major forms of communication firms use to supplement the information contained in their financial statements and other regulatory filings. Like many regulatory filings, earnings conference calls contain both quantitative and qualitative information. However, in contrast to the formal and even boilerplate language often seen in regulatory filings (e.g., annual and quarterly SEC reports), conference calls involve spoken language and are arguably more informative. Typically, a conference call starts with a brief introduction of the management team present on the call and a legal disclaimer about forward-looking statements. Then company executives (CEO, CFO, etc.) give an overview of the operating performance for the quarter just ended and provide information on future plans and operations. After the introductory statements by managers, the call is opened to questions from analysts and investors. Analysts' active participation in conference calls suggests that analysts seem to value information disclosed in conference calls.[14]

[13] JPS (2016), Joos and Piotroski (2017) and Hope et al. (2016) are other examples of recent papers that use the Morgan Stanley data.

[14] Matsumoto et al. (2011), Mayew and Venkatachalam (2012), Chen et al. (2014) and BCH (2017) are examples of recent studies that focus on the information value of earnings conference calls to investors.

3 Sample, data and methodology

3.1 Matched sample procedure

We build our sample by merging data from samples of analyst investment reports and transcripts of earnings conference calls. The first sample 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.[15] The second sample contains quarterly earnings conference call transcripts from *www.seekingalpha.com* for the period from 2006 to 2013. Seeking Alpha is one of the largest investor-oriented websites in the United States that covers a broad range of publicly-traded companies and provides free access to earnings conference call transcripts.[16] We match the samples in calendar time by linking observations if they appear in both samples. To be precise, we match a Morgan Stanley report with an earnings call transcript if the Morgan Stanley report is published within 30 days of the earnings call date.[17] This procedure results in a matched sample of 4,336 reports, drawn from 624 unique firms and 125 individual analysts, over our sample period.

As an example of how the earnings announcement and conference call information is connected with the analyst notes, we refer again to the investment note from which Figure A1 is taken. This note contains a detailed section covering the results discussed during the earnings conference call. In particular, Figure A2 shows a table where the analyst benchmarks the results of the firm with expectations. The discussion of the information received during the earnings conference call is presented in two sections called "What we liked" and "What we didn't like". These sections cover the topics of relevance discussed in the conference call with headlines such as : "Strong revenue growth continued, driven by Electronics and other General Merchandise"; "Mobile eCommerce ramping faster than we thought";"North America gross margin stronger than expected"; "Despite iPad launch, Kindle device + content growth remained stellar"; "Lower-than-expected operating margin owing to incremental fullfillment & marketing/G&A expenses."

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

[16] Seeking Alpha was founded in 2004, but a comprehensive coverage of firms on the website started in 2006.

[17] While we use a 30-day criterion to match the samples, 74% of reports are published within 2 days following an earnings call. See also Huang et al. (2017) for a discussion of the timing of investment reports immediately following earnings conference calls.

3.2 Variable definitions and descriptive statistics

3.2.1 Morgan Stanley investment report variables

Morgan Stanley requires its analysts to provide three value estimates for each firmthe base case, the bull case and the bear case when issuing a company investment report. We define the variables *Base*, *Bull* and *Bear* as the analysts' per-share equity valuation estimate under each of these three scenarios, respectively. 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 analysts' beliefs about firm value under alternative scenarios. 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 a recession. Taken together, the three scenarios *Base*, *Bull* and *Bear* convey the analyst's beliefs about the distribution of the potential valuation outcomes under different conditions.

We use the values of the three scenario-outcomes to define our proxy for the analyst's fundamental risk forecast. In particular, we create the variable *Spread*, measured as the difference between *Bull* and *Bear*, scaled by the average of *Bull* and *Bear*. As defined, *Spread* captures the relative range in the state-contingent value estimates as a percentage of the midpoint of the analysts' valuation range. By construction it is independent of both current prices and the magnitude of base-case price appreciation. *Spread* is analogous to the "cone of uncertainty" that exists in many professional forecasting settings; it conveys information about the potential distribution of future prices, with the cone centered around the analysts' base-case valuation and bounded by the bull- and bear-case valuations. The interpretation of *Spread* is straightforward: the tighter the distribution at the report date, the more certain the analyst is about the firm's value and payoffs; the wider the distribution, the greater the uncertainty about state-contingent risk surrounding value and payoffs. As measured, our main variable *Spread* uses information obtained from an investment report that is matched with a particular earnings conference call.

Beyond the *Spread* metrics, we use the scenario-based valuation estimates to calculate a number of additional variables. First, we compute *Base Return* to reflect the anticipated price appreciation associated with investing in the firm at the time of the analyst report: *Base Return* is measured as *Base* minus *Price*, scaled by *Price*, where *Price* is the closing stock price on the day before the report is released. This metric is analogous to the traditional *Target Price* return used in analyst research (e.g., Bilinski et al. (2012), Bradshaw et al. (2013), and JPS (2016)). Second, we create the variable *Tilt*, measured as the difference between *Base* and *Bear*, scaled by the difference between *Bull* and *Bear*, to capture the extent to which the base case is tilted towards the bull or bear case (Joos and Piotroski, 2017). As constructed, *Tilt* is bounded between zero and one, with *Tilt* equal to 0.5 when the firm's upside and downside scenarios are distributed symmetrically around the base case and converging towards one (zero) as the base-case valuation moves towards the bull (bear) case.

3.2.2 Earnings conference call variables

Our research design aims to connect the quantitative and qualitative information contained in the earnings conference calls with the earlier defined scenario-based forecasts of fundamental risk. To capture the former we first compute the unexpected earnings (*UE*) associated with the earnings conference call as the actual earnings per share (EPS) minus analyst consensus forecast of one- or two-quarters-ahead earnings issued or reviewed in the last 60 days before earnings announcement, divided by stock price at the end of quarter. Our main metric of quantitative information is the absolute value of *UE* or *AbsUE*. We complement this variable and capture the direction of the quantitative information in the earnings conference call using an indicator variable *GoodNews* that is equal to 1 if *UE* is positive, and 0 otherwise.

To capture the qualitative content of the earnings call, we focus on linguistic tone. We use Loughran and McDonald (2011)'s financial sentiment dictionary (hereafter, L&M dictionary) to identify positive and negative words in the earnings call.[18] The L&M dictionary was created to analyze qualitative (i.e., soft) information in financial contexts and is now widely used among researchers to gauge linguistic tone (see for example, Feldman et al. (2009); Dougal et al. (2012); Liu and McConnell (2013); Chen et al. (2014); Kearney and Liu (2014)).[19] We calculate firm-specific tone of earnings conference call as the number of positive words minus the number of negative

[18]We adopt a word-frequency approach to gauging qualitative information from earnings conference calls. While different, more complex approaches to measuring qualitative information have been developed, two recent papers, Henry and Leone (2016) and Loughran and McDonald (2016) discuss potential drawbacks associated with these different techniques.

[19]Loughran and McDonald (2011) emphasize the importance of using domain-specific dictionaries and show that their word lists work well at capturing tone in financial reports such as 10-Ks and 10-Qs, IPO prospectuses, etc. See http://www3.nd.edu/~mcdonald/Word_Lists.html.

words divided by the total number of words in the conference call:

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

Intuitively, *Tone* captures the extent to which earnings conference call participants (managers, analysts and investors) exhibit optimism regarding current firm performance and future prospects. In our additional analyses, we refine our definition of *Tone* to gain more insights about its usefulness. Specifically, we use the methodology in BCH (2017) to define measures of *ExtremeTone* and *ModerateTone*. We also use XML tags in the transcripts of the earnings call to calculate *Tone* corresponding to the presentation and questions and answers sections of the call as well as to each call participant.

3.2.3 Descriptive statistics on sample characteristics

Table 1, Panel A provides descriptive statistics on our main variables of interest. The panel shows that average *Spread* in our sample is 0.69 with a standard deviation of 0.30, suggesting that our sample observations exhibit considerable variation in our metric of fundamental risk forecasts. Further, average *BaseReturn* is 15.5% and average *Tilt* is 0.55 (standard deviation of 0.28 and 0.13, respectively). Consistent with previous research, both metrics point to optimistic target price forecasts, given market performance over the period studied and tilt of the target prices towards the bull case (see (Joos and Piotroski, 2017)). The evidence on *UE*, *AbsUE* and *Goodnews* suggests that on average the earnings calls present positive earnings surprises (67% of observations). The panel further shows that earnings conference calls are, on average, optimistic: the average *Tone* in our sample is 0.50 (standard deviation of 0.61). This descriptive summary is consistent with findings in BCH (2017) that conference call participants tend to use more positive than negative words in their discussions.

When assessing the role of our metrics of quantitative and qualitative information in the earnings conference call, we control for a number of firm attributes that relate to equity risk and analysts' assessments of firm risk in the analysis (e.g., Beaver et al. (1970); Fama and French (1992); Lui et al. (2007), JPS (2016)). These firm characteristics include: 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. We provide formal definitions of all variables in Table A1.

Table 1, Panel B presents descriptive statistics for these variables in the sample. Consistent with prior research the firms in our sample are large (average market cap is $8.3bn) and exhibit high growth prospects (average *BTM* is 0.52). Average *Beta* in the sample is 1.22 and average *IdioRisk* of 0.51 points to important idiosyncratic return behavior for the sample observations. Around 14% of the observations are *Loss* firms. Finally, across the sample period, the average *VIX* value was 26, with an interquartile range going from 18 to 27. Table 2 presents univariate Pearson correlations between our variables of interest. The first column in the Table shows that *Spread* exhibits a strong negative univariate relation with *UE* and *GoodNews*, a positive relation with *AbsUE*, and a negative relation with *Tone*. In other words, on a univariate basis the correlations between *Spread* and our metrics of quantitative and qualitative information are strongly related. All other control variables (with the exception of *IdioRisk*) exhibit strong univariate relations with *Spread* as well.

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 conference calls. Section 4.1 discusses our baseline results while section 4.2 augments these analyses with a focus on the role of macro-uncertainty. Section 4.3 presents our analysis of the relation between our information metrics and *ex post* absolute valuation errors. Section 5 presents additional analyses that complement these main results.

4.1 Relation between Spread, Unexpected Earnings, and Tone of the earnings conference call

4.1.1 Univariate evidence

Table 3 presents descriptive evidence on the relation of interest using *Spread* as our measure of expected fundamental risk. To carry out this analysis, we start by independently sorting our sample observations into three portfolios based on the terciles of the distribution of *UE* in Panel A and three portfolios based on the terciles of the distribution of *Tone* in Panel B. Similarly, Figure 1 shows the relation between *Spread* and both *UE* and *Tone*. Panel A shows the average values of *Spread* across the terciles of *UE*. The panel shows that *UE* exhibits a non-linear U-shaped relation with *Spread*: *Spread* is larger in the outer terciles and smaller in the middle tercile of the *UE* distribution. In fact, the t-stat on the difference between average Spread in the outer terciles is -0.66. This evidence is consistent with analysts mapping larger deviations of earnings from expectations into larger estimates of future fundamental risk, regardless of the nature of earnings news (good vs bad). Panel B shows that *Tone* exhibits a different relation with *Spread*. In this case, Spread exhibits a monotonic, negative relation with *Tone*: analysts map a more positive *Tone* of the earnings conference call into smaller estimates of future fundamental risk. The difference between average *Spread* in the outer deciles in this case is around 22% (0.76/0.62 - 1) and is highly significant (t-stat=6.83). This finding is consistent with the evidence in Kothari et al. (2009) of a negative relation between the tone of disclosures and proxies for firm risk.

Table 3, Panel C extends the evidence in Panels A and B by double-sorting on both *UE* and *Tone* and by showing average *Spread* in each of the 9 portfolios obtained. The evidence in the panel suggests that both metrics of information complement each other. For each level of *Tone*, *UE* exhibits the U-shaped relation with *Spread* we observed earlier in Panel A. The differences in *Spread* across outer *UE* terciles controlling for *Tone* portfolios are significant only when *Tone* is high, i.e., more positive. By contrast, for each level of *UE*, *Tone* linearly ranks *Spread* leading to highly significant differences in *Spread* across outer *Tone* terciles.

The descriptive evidence on the relation between *Spread* and both *UE* and *Tone* therefore points to a complementary role for both information variables. We observe higher *Spreads* when earnings deviations from expectations are large (regardless of their sign) and *Tone* is more negative;

in contrast, analysts appear to forecast the smallest *Spreads* when earnings surprises are lowest (median tercile of *UE*) and *Tone* is more positive. One take-away from this evidence is that large positive earnings surprises do not necessarily imply that analysts moderate their view on future fundamental risk of the firm.

4.1.2 Regression results

The descriptive results in Table 3 provide initial evidence that both *UE* and *Tone* relate to estimates of future fundamental risk. To verify the robustness of these initial descriptive results and also control for firm attributes that relate to equity risk and analysts' assessments of risk, we estimate various specifications of the following model:

$$\begin{aligned} Spread = \alpha_0 &+ \alpha_1 AbsUE + \alpha_2 Tone + \alpha_3 GoodNews + \alpha_4 BaseReturn + \alpha_5 Tilt + \alpha_6 Beta + \\ &\alpha_7 IdioRisk + \alpha_8 Loss + \alpha_9 EarnVol + \alpha_{10} FirmSize + \alpha_{11} BTM + \\ &\alpha_{12} Leverage + \alpha_{13} NegBV + \alpha_{14} BTM \times NegBV + \alpha_{15} Leverage \times NegBV + \\ &\beta_1 AnalystFE + \beta_2 IndustryFE + \beta_3 YearQuarterFE + \varepsilon. \end{aligned} \tag{1}$$

In this regression, our main variables of interest are *AbsUE* and *Tone*. As a first control, we include *GoodNews* in all specifications to control for the direction of the information in the deviation of earnings from expectations. Following JPS (2016), we also include controls for the analysts' estimates of expected return and tilt of the target price in the equation: *Base Return* and *Tilt*. Finally, consistent with Lui et al. (2007) and JPS (2016) we include the discussed selection of control variables in the models. Finally, all regressions contain fixed effects for analysts, year-quarter and industry. We base our industry variable on the Fama-French 12 industry classification (FF12).[20]

With respect to the main variables of interest, Table 4 shows that across specifications the coefficients on *AbsUE* are significantly positive: larger deviations of earnings from expectations map into larger forecast of future fundamental firm risk. In contrast, the coefficients on *Tone* are significantly negative in all specifications, consistent with a more positive tone in the earnings conference call reducing estimates of future fundamental firm risk.[21]

[20] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_12_ind_port.html. Our results are the same when we use Fama-French 48 or SIC two-digit industry classifications.

[21] We carry out our main analyses with L&M's dictionary as it has been validated in previous research. In unt-

In Table 4, the coefficients on most of the control variables are also significant across all specifications and point to some interesting findings. The negative and significant coefficients on *GoodNews* indicate that positive earnings surprises have a directional effect on estimates of future fundamental firm risk, beyond the 'shock' effect of the magnitude of the deviation. Further, consistent with JPS (2016), both *BaseReturn* and *Tilt* exhibit significant positive (negative) coefficients. The positive coefficients on *BaseReturn* are consistent with analysts modeling a risk-return trade-off in their forecasts, while the negative coefficients on *Tilt* are consistent with more positive tilts reflecting more analyst conviction (JPS, 2016). Finally, the coefficients on the other controls in the specification are consistent with the findings in Lui et al. (2007) and JPS (2016) and show that *Spread* is significantly associated with observable firm characteristics related to the riskiness of the firm's operations and long-term value. *Spread* increases in the firm's exposure to both systematic and idiosyncratic risk. *Spread* also relates positively to beta and book-to-market ratios and negatively to firm size, consistent with the risk-based interpretation for Fama and French (1992)'s three-factor model. *Spread* is incrementally larger for highly levered and loss making firms, suggesting that analysts consider firm-specific, fundamental factors beyond those outlined in traditional asset pricing models (e.g., CAPM and Fama-French three-factor model) when assessing the distribution of potential payoffs to the firm.

The regressions in Table 4 use a sample of *Spread* observations published within a month subsequent to earnings conference calls with the mean (median) number of days between the earnings conference call and the investment report being 3 (1) days. The timing requirement therefore closely links the investment reports in the sample to particular earnings conference calls. Additionally, we include the control variables and fixed effects in the multivariate setting to mitigate the concern that *AbsUE* and *Tone* pick up information not specifically related to the earnings conference call. In further untabulated analyses, we also augment the specification with a lagged variable of *Spread* taken from investment reports published prior to the earnings conference call. When we include this variable its coefficient is positive and highly significant but, importantly, none of our main results on the other variables is affected by this inclusion.

abulated tests, we verify that our results are not dictionary-specific. Loughran and McDonald (2016) note that the language in earnings conference calls potentially differs from the language in regulatory filings. We therefore use BCH's (2017) expanded dictionary of positive and negative words and their extremity rankings to construct an alternative measure of *Tone*. Our inferences remain the same - more positive tone results in lower estimates of future fundamental risk.

Taken together, our findings in Table 4 corroborate our earlier descriptive results that both *AbsUE* and *Tone* exhibit a complimentary relation with estimates of future fundamental risk. Our regression result on *Tone* corroborates our earlier descriptive finding in Table 3 and supports our prediction of a negative relation between disclosure tone and proxies of firm risk, similar to the evidence in Kothari et al. (2009), Campbell et al. (2014) and Campbell et al. (2017). Importantly, our finding suggests that when modeling forecasts of future fundamental firm risk, analysts do not just focus on quantitative information but also assimilate qualitative information in the earnings conference call.

4.2 Role of macroeconomic uncertainty

After establishing our baseline results, we explore next whether the relation between *AbsUE* or *Tone* and *Spread* changes as a function of the level of macro-uncertainty present at the time of the forecast. Following previous research, we identify circumstances characterized by heightened macro-uncertainty via two proxies. The first proxy captures sample observations made during periods with elevated values of the VIX index (*High VIX*), while the second one identifies sample observations in recession periods as defined by the National Bureau of Economic Research (NBER) (*Crisis*). Table 5 shows descriptive evidence on the behavior of our main variables across sample partitions based on the proxies *HighVix* and *Crisis*. We observe that both proxies are related: 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. The table further shows that both *HighVIX* and *Crisis* significantly affect the three main variables. In particular, we observe that *Spread* widens significantly in periods of *HighVix* and *Crisis*.

The differences in *Spread* are highly significant across both partitions (untabulated t-stats are 11.57 and 11.40 for VIX and crisis specifications,respectively).[22] Next, we observe that both metrics of information are affected by *HighVix* and *Crisis*: average *Tone* drops while the average *AbsUE* increases significantly in periods marked by *HighVix* or *Crisis*. All t-stats on differences point to high statistical significance. The descriptive evidence therefore suggests that our proxies *HighVix* and *Crisis* identify observations that present challenging forecast circumstances with larger shocks to expected earnings and a more negative tone of earnings conference calls. The proxies also mark

[22]The differences in *Spread* across macro-uncertainty regimes are economically significant as well. In both panels A and B, the difference is approximately 17% (0.745/0.638-1 and 0.768/0.655-1, respectively).

substantially increased forecasts of future fundamental firm risk by analysts.

We now formally test whether these changing circumstances affect the relation between our two metrics of quantitative and qualitative information and the resulting *Spread* forecasts by augmenting equation (1) as follows:

$$\begin{aligned} Spread &= \alpha_0 + \alpha_1 AbsUE + \alpha_2 Tone + \alpha_3 HighVIX \times AbsUE + \alpha_4 HighVIX \times Tone + \\ &\quad + CONTROLS + \varepsilon, \\ Spread &= \beta_0 + \beta_1 AbsUE + \beta_2 Tone + \beta_3 Crisis \times AbsUE + \beta_4 Crisis \times Tone + \\ &\quad + CONTROLS + \varepsilon. \end{aligned} \tag{2}$$

CONTROLS are the same as in equation (1). The variables of interest are the two interactive variables that combine our metrics of information with the proxies for high macro-uncertainty settings. Table 6, Panel A reports on the specification with the *HighVix* proxy. The table shows that both baseline results on *AbsUE* and *Tone* hold as before, but that only the coefficients on the interaction variables with *Tone* are statistically significant. The sign on these coefficients is negative indicating that the *HighVix* circumstances exacerbate the negative relation between Tone and *Spread*. In contrast, the results further show that the coefficients on the interactions of *AbsUE* and *HighVIX* are not significantly different from zero, consistent with *HighVIX* conditions having no effect on how analysts map the quantitative information in *AbsUE* into estimates of *Spread*. The role of the control variables in the regression specifications remains largely unchanged.

Panel B reports on the specification with the *Crisis* proxy and shows results that are very similar to those in Panel A. In all specifications of panel B we observe positive (negative) coefficients on *AbsUE* (*Tone*) as before. In addition, the coefficients on the interaction of *Tone* and *Crisis* are highly significant and negative, leading to the same conclusion that *Crisis* observations exacerbate the negative relation between *Tone* and *Crisis*. As in Panel A, the coefficients on the interaction between *AbsUE* and *Crisis* are not statistically significant.

Taken together, the evidence on the role of macro-uncertainty in Tables 5 and 6 leads to two important insights. First, heightened levels of macro-uncertainty affect all three main variables in the analyses. Second, analysts appear to strengthen the assimilation of qualitative information into their forecasts for fundamental firm risk in circumstances of higher macro-uncertainty, whilst leaving the extent of incorporation of quantitative information unchanged.[23] This particular finding extends earlier evidence on higher analyst effort in times marked by higher volatility and uncertainty documented by Loh and Stulz (2016) and evidence on changing determinants of *Spread* in the financial crisis documented by JPS (2016). Loh and Stulz (2016) argue that analysts "change what they do" in bad times. We concur and extend the results in Loh and Stulz (2016) by showing that not only analysts work harder, they also appear to alter the mix of quantitative vs qualitative information as inputs to their forecasts.[24] In this way, our findings are also consistent with Garcia (2013) who shows that a measure of sentiment becomes a stronger predictor of stock returns during economic downturns.[25]

Our evidence in Tables 5 and 6 showing the effect of macro-uncertainty on the forecasting process of analysts also complements previous research that draws attention to the role of firm-specific uncertainty for forecast properties and the informativeness on analyst reports (e.g., Frankel et al. (2006), Loh and Stulz (2011)). While our specification in Table 6 includes variables that capture firm-level uncertainty, we carry out a robustness check using an additional metric of firm-level uncertainty based on the volatility of firm-level daily returns. We define *HighVol* as an indicator variable that takes the value of 1 if the firm has a daily return volatility level over the past month higher than the sample median. Using this variable we estimate two additional (untabulated) specifications. When we use *HighVol* instead of *HighVix* or *Crisis*, we find that *HighVol* exacerbates the relation between both *AbsUE* and *Tone* and *Spread*: the coefficients on the interaction terms of *HighVol* and *AbsUE* (*Tone*) are reliably positive (negative) and statistically significant. Further, we get similar results when we control for *HighVix* and *Crisis* and their interaction terms with *AbsUE* and *Tone*. These results suggest that when firm-level uncertainty is high, analysts place greater emphasis on both quantitative and qualitative information when making their forecasts for fundamental firm risk.

[23] The implied coefficients on *Tone* during periods of *HighVix* or *Crisis* imply a change of about 0.05 in *Spread* (or about 7% of average *Spread*) for each standard deviation change in *Tone*.

[24] Our results for both *HighVix* and *Crisis* hold when we include both variables simultaneously in the specification of equation (2).

[25] Similar to our *Tone* metric, Garcia (2013) constructs a measure of sentiment based on a count of positive and negative words. In his case the source of information is the financial news reported in the *New York Times*.

4.3 Relation between quantitative and qualitative information in earnings conference calls, Spread, and Absolute Valuation Error

The previous analyses examine the relation between our metrics of information and *ex ante* forecasts of firm risk. We now complement these analyses with a focus on how the inclusion of quantitative and qualitative information into the risk forecasts affects their predictive ability. To do so, we build on the analysis in JPS (2016) and study the relation between *Spread* and absolute valuation errors (*AbsValErr*), defined as the absolute value of base return forecast errors (see Table A1). JPS (2016) document a positive relation between *Spread* and *AbsValErr* that strengthens after the financial crisis and interpret this result as evidence of improved calibration of the *Spread* forecasts.

To assess the role of quantitative and qualitative information in this context, we estimate a path analysis of the relation between *AbsUE* and *Tone* and *AbsValErr* with a mediating role for *Spread*. The path analysis allows us to model the sequential nature of earnings conference calls and analyst reports and differentiate between the direct and indirect (via *Spread*) effects of our earnings call information on subsequent *AbsValErr*. Panel A of Table 1 shows that the mean (median) of *AbsValErr* is 0.35 (0.26) for the full sample.[26] In Panel A of Table 7, we report the results of our path analysis for the full sample. Consistent with the findings in JPS (2016), we find a significant positive relation between *Spread* and *AbsValErr*. We also find that *AbsUE* has both a direct and indirect effect via *Spread* on *AbsValErr*, suggesting that the information in earnings surprise is not fully subsumed by analysts' risk forecasts. In addition, we find that *Tone* is indirectly related to *AbsValErr* through *Spread*, while there is no direct relation for the full sample. This suggests that *Tone* contributes to the calibration of *Spread* thus affecting the resulting positive relation between *Spread* and *AbsValErr*.

To measure the impact of conditions of heightened macro-uncertainty on the relations of interest, we re-estimate the path analysis using two sub-samples reflecting different levels of macro-uncertainty. For reasons of parsimony, we use both our proxies for macro-uncertainty simultaneously and classify observations in 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).[27] Panel

[26] These values are comparable to what JPS (2016) report, albeit somewhat lower.

[27] Untabulated analyses show that the different settings of macro–uncertainty affect the magnitude of *AbsValErr*. Mean (median) *AbsValErr* is 0.41 (0.33) and 0.27 (0.20) in the High and Low Macro-Uncertainty sub-samples, respectively.

B of Table 7 shows sharp differences between the patterns of the path analysis in each sub-sample. In particular, both quantitative and qualitative information exhibit strong direct and indirect effects on *AbsValErr* under conditions of high macro-uncertainty, but not under conditions of low macro-uncertainty.

Pertinent to the question of whether the inclusion of *AbsUE* and *Tone* affects the predictive ability of *Spread*, Panel B shows that the pattern of indirect effects across both sub-samples varies strongly. While the indirect effects of both *AbsUE* and *Tone* are significant at the 10% level in the Low Macro-Uncertainty sub-sample, they become highly significant at the 1% in the High Macro-Uncertainty sub-sample. Further, the increase of importance of the indirect effect across sub-samples is more pronounced for *Tone* than for *AbsUE*: the mediating path coefficient on *Tone* changes from -0.050 to -0.144 (or almost a threefold rise in magnitude) whereas the corresponding coefficient on *AbsUE* increases from 0.115 to 0.140. The resulting change in pattern of the indirect effect of both variables is even more pronounced as it not only reflects the difference in mediation, but also the increase in the role of *Spread* across sub-samples. Figure 2 graphs the results presented in Table 7.

Taken together, the path analysis sheds light on the role of quantitative and qualitative information in the context of JPS's (2016) finding of a positive relation between analysts' *ex ante* forecasts of risk, i.e., *Spread*, and *ex post* valuation error, i.e., *AbsValErr*. Importantly, the pattern of results shows that the improvement in calibration of *Spread* under conditions of macro-uncertainty, i.e., the strengthening of the relation between *Spread* and *AbsValErr*, is a function of both quantitative and qualitative information. However, the results also highlight that conditions of macro-uncertainty have a stronger impact on the role and significance of qualitative information than on the role of quantitative information.

5 Additional analyses

Our analyses so far provide evidence on the relation between one metric of qualitative information in earnings conference calls, namely *Tone*, and forecasts of fundamental firm risk. While *Tone* captures a relevant feature of the language used in the earnings conference calls, our focus on this single variable presents limitations along several dimensions. First, since *Tone* is measured as the difference between the frequency of positive and negative words in the earnings conference call the variable represents a net number. As such the net number obscures different combinations of positive and negative word frequencies. Going back to Tetlock (2007), the textual analysis literature however often emphasizes the occurrence of negative words to construct their main variables of interest.[28] In a first additional analysis, we therefore refine our *Tone* variable by separately capturing the frequency of positive and negative words in the earnings call.[29] Second, as BCH (2017) underline, *Tone* is an important attribute of language but it is also limited since language is not binary (e.g., good vs excellent). Therefore, we refine our *Tone* measure to capture extreme vs moderate portions of *Tone*. Further, our variable *Tone* captures only the overall tone of the earnings conference call observations. In other words, it does not distinguish between the tone(s) in the different parts of the earnings conference call, most notably the management presentation (i.e., the prepared remarks) part vs the Q&A part of the conference call. Finally, and in relation to the Q&A part of the conference call, *Tone* does not distinguish between the source of the tone, i.e., management vs the analysts on the call. We now turn to a number of analyses that address these limitations of the variable *Tone* to deepen our understanding of how the *Tone* of earnings conference calls maps into the analyst forecasts of fundamental firm risk.

5.1 Focus on positive vs negative words

We refine our metric *Tone* by focusing on positive and negative word counts separately. Specifically, we define *PosTone* and *NegTone* as the number of positive and negative words in the conference call divided by the total number of words. Splitting *Tone* into its positive and negative components allows us to see whether analysts pay attention to the choice of words in the conference call. Using these two additional metrics, we re-estimate modified specifications of equation (1) and include both *PosTone* and *NegTone* to replace the single variable *Tone*.

Table 8, Panel A presents the results. Across all specifications, the coefficients on *PosTone* (*NegTone*) are negative (positive) and statistically significant. These findings therefore confirm and extend our earlier results on the directional negative relation of *Tone* with forecasts of risk. The relation between *Tone* and forecasts of risk works symmetrically and is consistent with results

[28] See also Tetlock et al. (2008) and Loughran and McDonald (2011), among others.

[29] Relatedly, in their study of managerial affective states, Mayew and Venkatachalam (2012) also differentiate between positive and negative affect in their research design.

in Tetlock (2007) and BCH (2017). Importantly, this finding also mitigates the concern expressed by Loughran and McDonald (2016) (Section 6.3) that the use of a net measure of *Tone* potentially leads to ambiguous results as the usage of positive words is often used to frame a negative statement. In untabulated tests, we repeat our analysis on the role of macro-uncertainty reported in Table 6 using specifications of the model that include *PosTone* and *NegTone* instead of *Tone*. In all specifications, our previous results hold: the coefficients on the interactions terms of the tone variables and *HighVix* or *Crisis* are all significant and point to macro-uncertainty strengthening the relation between qualitative variables and *Spread*. By contrast, the coefficients between *AbsUE* and the macro-uncertainty variables remain non-significant. Taken together, our finding of a symmetric effect of positive and negative tone complements previous research that often emphasizes the importance of negative tone only (e.g., Loughran and McDonald (2016)).

5.2 Focus on linguistic extremity

To refine the binary measure of *Tone*, BCH (2017) develop a dictionary of linguistic extremity in earnings conference calls. Using a similar sample of earnings conference calls, BCH document that market participants respond more strongly to extreme rather than moderate language. Building on this evidence, we adopt BCH's definition of extreme language and calculate *ExtremeTone* and *ModerateTone*. Intuitively, *ExtremeTone* captures not only positivity or negativity, but also measures the strength of statements in the call (e.g., very good performance, amazing job, terrible quarter, major failure, etc.). Consistent with BCH, we define *ExtremeTone* (*ModerateTone*) as the number or extreme (moderate) positive minus the number of extreme (moderate) negative words scaled by the total number of words in the conference call. Using these metrics, we then re-estimate modified specifications of equation (1) and include both *ExtremeTone* and *ModerateTone* to replace the single variable *Tone*.

Table 9 presents select coefficients from different specifications of equation (1). We observe that across specifications only *ExtremeTone* obtains negative and significant coefficients, in line with our earlier findings of a negative and significant coefficient on the single variable *Tone*. Across specifications, the coefficient on *ModerateTone* is not significantly different from zero. As before, the coefficients on *AbsUE* remain positive and significant in these augmented specifications.

Our finding sharpens our earlier evidence on the relation between the overall tone in the earnings conference call and analysts' forecasts of fundamental firm risk. It underlines the importance of linguistic extremity and suggests that when forecasting fundamental firm risk mainly extreme language affects the analyst forecasts. The finding also complements the results in BCH on the relation between linguistic extremity and analyst forecast revisions of earnings following earnings conference calls. BCH find that *ExtremeTone* is more strongly associated with analyst forecast revisions of earnings than *ModerateTone*. They interpret their result to be consistent with findings in the psychology literature that information presented in more extreme way can be more persuasive and impact judgments more strongly (Nisbett and Ross (1980), Hosman (2002)). Taken together, when we refine the definitions of the tone variables to reflect the intensity of the language used in the earnings conference calls our results hold for both quantitative and qualitative information metrics. However they also emphasize the role of linguistic intensity for risk forecasts by suggesting that moderate tone lacks the *conviction* to influence risk forecasts, whereas extreme tone carries sufficient persuasion and credibility to affect analysts' perception of future firm risk.

5.3 Focus on tone in different parts of the earnings conference call

Next, we extend our research design to distinguish between the tone of the different parts of the conference call. Research on earnings conference calls has generally concluded that the interactive nature of these calls contributes to their informativeness.[30] Consistent with these findings, the evidence in Brown et al. (2015) suggests that analysts distinguish between the Q&A part and the presentation portion of earnings conference calls in their assessment of the usefulness of these calls for their forecast generating process: Table 3 in Brown et al. (2015) list the Q&A (presentation) portion as the second (fourth) in a list of 'useful' items in this context. In addition, Lee (2015) distinguishes between the two parts of the conference call in his research design and finds that management's adherence to predetermined scripts during the Q&A part is interpreted negatively by the market. To examine if the tone from the two parts of the earnings conference call has a different effect on the analyst forecasts of firm risk we define two variables, *ToneIntro* and *ToneQ&A*. These variables measure the tone from the management presentation and the Q&A part of the earnings conference call, respectively.

The results in Table 10, Panel A, show that when we expand equation (1) to include *ToneIntro*

[30] See for example Tasker (1998), Frankel et al. (1999), Bowen et al. (2002), Bushee et al. (2003), Matsumoto et al. (2011), and Lee (2015).

and *ToneQ&A*, we obtain significantly negative coefficients on both variables. However, the panel also shows that these coefficients are comparable in magnitude and therefore suggest that both parts of the earnings conference call contribute to the analyst forecasts of future firm risk. Since both tone variables are highly correlated, we also estimate a different specification using *ToneIntro* and orthogonal *ToneQ&A*, where the latter is the residual from a regression of *ToneQ&A* on *ToneIntro*. In other words, orthogonal *ToneQ&A* is the complementary component to *ToneIntro*. When we re-estimate equation (1) using *ToneIntro* and orthogonal *ToneQ&A*, both variables obtain significant negative coefficients, consistent with the tone in both parts of the earnings conference call mapping into analyst forecasts of future risk.

The fact that the tone of both parts of the call matter for the estimates of future fundamental firm risk is important given the evidence in Mayew et al. (2013) that analysts participating on earnings calls possess superior private information relative to analysts that do not participate. If these participating analysts therefore possess strong priors about future fundamental firm risk, the tone of their participation on the call will partially set the tone of the entire conference call. Our evidence though shows that the tone of management's prepared remarks, which precede the participation of the analysts on the call, affects estimates of future fundamental firm risk, thereby alleviating these potential concerns of reverse causality between *Tone* and *Spread*.

5.4 Focus on tone used by different participants of the earnings conference call

Expanding our analyses with a focus on the tone in the two parts of the earnings conference call has the additional advantage that we can differentiate between portions of the Q&A part pertaining to the different parties, i.e., management and participating analysts. We therefore separately measure tone of management responses (denoted by *ExecToneQA*) and tone of analyst questions and comments (denoted as *AnaToneQA*) in the Q&A section. Specifically, we take the difference between positive and negative word counts for the management (analyst) portion of the Q&A and scale it by the total management (analyst) words.

The last column in Table 10 shows the results when we expand our earlier specifications to include *ExecToneQA* and *AnaToneQA*. To exclude information from introductory remarks in the conference call, we orthogonalize both *ExecToneQA* and *AnaToneQA* with respect to *ToneIntro*. The relative magnitude of the coefficients show that the tone of both parties during the Q&A part of the call is related to analyst forecasts of future risk. This finding suggests that the tone of the analysts speaking on the call influences the viewpoints of the analysts modeling forecasts for the firms covered, even though the latter might not be participating or even be present on the call.

6 Conclusion

In this paper, we document how analysts incorporate both quantitative and qualitative information from earnings conference calls into their forecasts of fundamental firm risk. Our measure of the quantitative component of the calls gauges shocks to expected earnings, while our measure of the qualitative component of the calls captures the optimism of language in the conference call. Using information metrics, we establish two main results. First, we find that both quantitative and qualitative information maps into analyst forecasts of fundamental firm risk. Specifically, we find that analysts' perceptions of firm risk are lower (higher) when earnings conference calls are more positive (negative) and absolute earnings surprise is small (large). Second, we find that the relative importance of qualitative information increases during times of high macroeconomic uncertainty. Additionally, we provide initial evidence that this increased reliance on qualitative information improves the calibration of risk forecasts during high uncertainty times.

We further refine our measure of qualitative information to establish a number of additional results that confirm the robustness of our main findings and deepen our understanding of how analysts incorporate *Tone* into their forecasts of fundamental firm risk. In particular, the additional results underline the relevance of both positive and negative language, the distinction between moderate and extreme language in conference calls, tone of different parts of the earnings conference call, and tone of both management and participating analysts on the call.

Taken together, our study emphasizes the role of quantitative and qualitative information in earnings conference calls for the forecasting process of sell-side analysts. Our evidence on this aspect of a public firm event both resonates with and complements the comments made by analysts on the importance of conference calls with management in the survey of sell-side analysts by Brown et al. (2015). We thus contribute to the literature that aims to open up the "black box" of the analyst forecasting process. Importantly, our findings on the relevance of the specific forecast context, i.e., the conditions of macro-uncertainty, highlight that to understand "what analysts do" research needs to consider aspects of the forecast setting beyond the particular strategic incentives or behavioral biases that affect analysts' forecast activities. In line with recent papers such as Bradshaw et al. (2016) and Loh and Stulz (2016), we believe that future research on analyst behavior can explore further what aspects of the forecast setting make the analyst job "difficult" and what actions analysts take to deal with this forecast difficulty.

References

Amiram, D., W. R. Landsman, E. L. Owens, and S. Stubben (2014). Analysts forecasts during periods of high market uncertainty. *Working Paper, Columbia University*.

Arand, D. and A. G. Kerl (2012). Analyst research and investor reactions: Evidence from the 2008 financial crisis. *Working Paper, University of Giessen*.

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.

Bochkay, K., S. Chava, and J. Hales (2017). Hyperbole or reality? investor response to extreme language in earnings conference calls. *Working Paper, University of Miami*.

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

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 (2016). 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.

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

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*, 396–455.

Campbell, J., H. S. Lee, H.-M. Lu, and L. Steele (2017). Is the variation of a manager's disclosure tone across time associated with investors' assessment of firm risk? *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.

Cutler, D. M., J. M. Poterba, and L. H. Summers (1989). What moves Stock Prices? *Journal of Portfolio Management 15*(3), 4 – 12.

Dougal, C., J. Engelberg, D. Garcia, and C. A. Parsons (2012). Journalists and the stock market. *Review of Financial Studies 25*(3).

Fama, E. F. and K. R. French (1992). The cross-section of expected stock returns. *the Journal of Finance 47*(2), 427–465.

Feldman, L., S. Govindaraj, J. Livnat, and B. Segal (2009). Managements tone change, post earnings announcement drift and accruals. *Review of Accounting Studies 15*(4), 915 – 953.

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

Frankel, R., S. Kothari, and J. Weber (2006). Determinants of the informativeness of analyst research. *Journal of Accounting and Economics 41*(1), 29–54.

Garcia, D. (2013). Sentiment during recessions. *The Journal of Finance 68*(3), 1267–1300.

Hales, J., X. J. Kuang, and S. Venkataraman (2011). Who believes the hype? an experimental examination of how language affects investor judgments. *Journal of Accounting Research 49*(1).

Henry, E. and A. J. Leone (2016). Measuring qualitative information in capital markets research: Comparison of alternative methodologies to measure disclosure tone. *The Accounting Review 91*(1), 153–178.

Hope, O.-K., D. Hu, and H. Lu (2016). The benefits of specific risk-factor disclosures. *Review of Accounting Studies 21*(4), 1005–1045.

Hope, O.-K. and T. Kang (2005). The role of other information in the valuation of foreign income for us multinationals. *Journal of Accounting, Auditing & Finance 20*(4), 355–377.

Hosman, L. A. (2002). Language and persuasion. *The persuasion handbook: Developments in theory and practice*, 371–390.

Huang, A., R. Lehavy, A. Zang, and R. Zheng (2017). Analyst information discovery and information interpretation roles: A topic modeling approach. *Management Science (Forthcoming).*

Huang, A., A. Zang, and R. Zheng (2014). Evidence on the information content of text in analyst reports. *The Accounting Review 89*(6), 2151–2180.

Jegadeesh, N., J. Kim, S. D. Krische, and C. Lee (2004). Analyzing the analysts: When do recommendations add value? *The Journal of Finance 59*(3), 1083–1124.

Joos, P. and J. D. Piotroski (2017). The best of all possible worlds: Unraveling target price optimism using analysts scenario-based valuations. *Working Paper, INSEAD and Stanford University*.

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.

Kacperczyk, M., S. Van Nieuwerburgh, and L. Veldkamp (2014). Time-varying fund manager skill. *Journal of Finance 69*(4), 1455–1484.

Kacperczyk, M., S. Van Nieuwerburgh, and L. Veldkamp (2016). A rational theory of mutual funds' attention allocation. *Econometrica 84*(2), 571–626.

Kearney, C. and S. Liu (2014). Textual sentiment in finance: a survey of methods and models. *International Review of Financial Analysis 33*, 171–185.

Kimbrough, M. D. (2005). The effect of conference calls on analyst and market underreaction to earnings announcements. *The Accounting Review 80*(1), 189–219.

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.

Lee, J. (2015). Can investors detect managers' lack of spontaneity? adherence to predetermined scripts during earnings conference calls. *The Accounting Review 91*(1), 229–250.

Li, F. (2006). Do stock markets investors understand the risk sentiment of corporate annual reports? *Working Paper, University of Michigan*.

Li, F. (2010a). The information content of forward-looking statements in corporate filings - a naïve bayesian machine learning approach. *Journal of Accounting Research 48*(5), 1049–1102.

Li, F. (2010b). Textual analysis of corporate disclosures: A survey of the literature. *Journal of Accounting Literature 29*, 143–165.

Liu, B. and J. J. McConnell (2013). The role of the media in corporate governance: do the media influence managers' capital allocation decisions? *Journal of Financial Economics 110*(1), 1–17.

Loh, R. K. and R. M. Stulz (2011). When are analyst recommendation changes influential? *Review of Financial Studies 24*(2), 593–627.

Loh, R. K. and R. M. Stulz (2016). Is sell-side research more valuable in bad times? Technical report.

Loughran, T. and B. McDonald (2011). When is a liability not a liability? *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.

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.

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. *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*.

Nisbett, R. E. and L. Ross (1980). Human inference: Strategies and shortcomings of social judgement.

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.

Roll, R. W. (1988). R-Squared. *The Journal of Finance 43*(3), 541 – 566.

Shiller, R. J. (1981). Do stock prices move too much to be justified by subsequent changes in dividends? *American Economic Review 71*(3), 421 – 436.

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*.

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

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. (2014). Asymmetric responses to earnings news: A case for ambiguity. *The Accounting Review 90*(2), 785–817.

Womack, K. L. (1996). Do brokerage analysts' recommendations have investment value? *The Journal of Finance 51*(1), 137–167.

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
Spread	Analyst's *Bull* forecast minus *Bear* forecast scaled by the average of *Bull* and *Bear*.	Analyst reports are from: Morgan Stanley
BaseReturn	The expected return (excluding dividends) to investing in the firm at the time of the analyst report, measured as *Base* minus *Price* scaled by *Price*, where *Price* is the closing stock price on the day before the release of the analyst report.	Morgan Stanley, FactSet
Tilt	Analyst's *Base* forecast minus *Bear* forecast, divided by *Bull* minus *Bear*.	Morgan Stanley
AbsValErr	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., *BaseReturn*).	Morgan Stanley, FactSet
UE	Actual earnings per share (EPS) minus analyst consensus forecast of one- or two-quarters-ahead earnings issued or reviewed in the last 60 days before earnings announcement divided by stock price at the end of quarter, winsorized at 1% and 99%.	IBES
AbsUE	Absolute value of *UE*.	IBES
GoodNews	Indicator variable that equals to 1 if *UE* is greater than 0.	IBES
Tone	Difference between positive and negative word counts scaled by total words in the earnings conference call ($\times$100).	Earnings calls are from: www.seekingalpha.com
ToneIntro	Difference between positive and negative word counts scaled by total words in the introductory section of the earnings conference call ($\times$100).	Earnings calls are from: www.seekingalpha.com
ToneQA	Difference between positive and negative word counts scaled by total words in the Q&A section of the earnings conference call ($\times$100).	Earnings calls are from: www.seekingalpha.com
PosTone	Number of positive words scaled by total words in the earnings conference call ($\times$100).	Earnings calls are from: www.seekingalpha.com
NegTone	Number of negative words scaled by total words in the earnings conference call ($\times$100).	Earnings calls are from: www.seekingalpha.com
ExtremeTone	Difference between extreme positive and extreme negative word counts scaled by total words in the conference call ($\times$100).	Earnings calls are from: www.seekingalpha.com

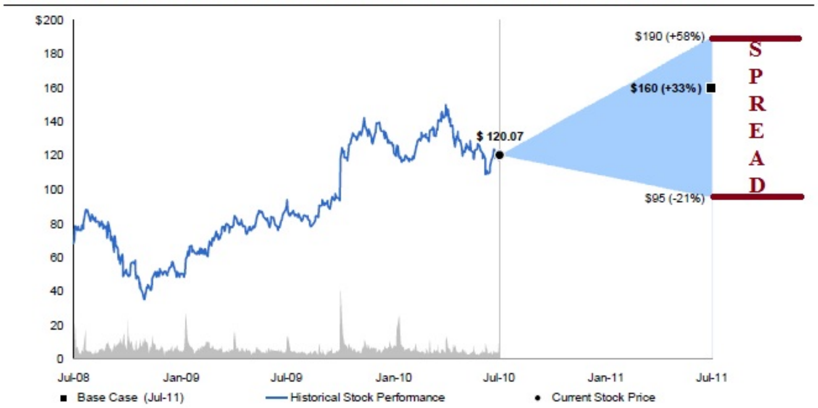
Table A1: Variable Definitions and Data Sources, continued

Variable	Definition	Source
ModerateTone	Difference between moderate positive and moderate negative word counts scaled by total words in the conference call (×100).	Earnings calls are from: www.seekingalpha.com
Beta	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 report).	FactSet
IdioRisk	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 report.	FactSet
Loss	Indicator variable equal to one if the sum of the past four quarterly earnings is negative, and zero otherwise.	COMPUSTAT
EarnVol	Standard deviation of firm earnings, calculated using earnings scaled by total assets in the last twenty quarters, with a minimum of eight quarters required.	COMPUSTAT
FirmSize	Natural logarithm of the market value of equity at the end of the previous quarter.	COMPUSTAT
BTM	Ratio of common equity to market value of the firm.	COMPUSTAT
Leverage	Long-term debt to total assets ratio.	COMPUSTAT
NegBV	Indicator variable equal to one if common equity is negative, and zero otherwise.	COMPUSTAT
VIX	Market volatility index around the time of analyst report.	CBOE
Crisis	Indicator variable equal to one if earnings conference call and analyst report are at the time of 2007-2009 financial crisis.	NBER

Figure A1: Example of Scenario-based Valuation

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

Risk-Reward View: Customer Focus Drives Sustainable Growth



Source: FactSet, Morgan Stanley Research

Bull Case $190	22x Bull Case 11E EV / EBITDA	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 $160	20x Base Case 11E EV / EBITDA	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 $95	16x Bear Case 11E EV / EBITDA	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	Weaknesses
1. Market / brand leadership in growing eCommerce 2. Best-in-class user experience defined by selection / convenience / reliability / low prices / free shipping / powerful recommendation engine 3. Leader in Internet innovation + logistics	1. Low prices / free shipping / product mix pressure near-term margins 2. High exposure to foreign exchange fluctuations 3. Seasonality + inventory risk
Opportunities	**Threats**
1. Continued share gains in overall retail market, in which eCommerce penetration is still low. 2. Continued expansion into international markets (both mature + emerging) 3. Monetization of nascent-stage initiatives gaining traction, such as Kindle, Amazon.com Web Services + digital downloads (VoD + Amazon.comMP3)	1. Apple and others present threat as media products transition to digital distribution 2. Execution risk in new markets / categories / products 3. Intense competition in both core (retail) + new markets (digital downloads, eCommerce solutions, web services, etc.) 4. Legal (e.g., state sales tax issues, international sales tax possibility)

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

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

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

Figure A2: Example of Scenario-based Valuation

AMZN — CQ2:10E vs. CQ2:10A Snapshot

(US$ in Thousands, Except per Share Data)

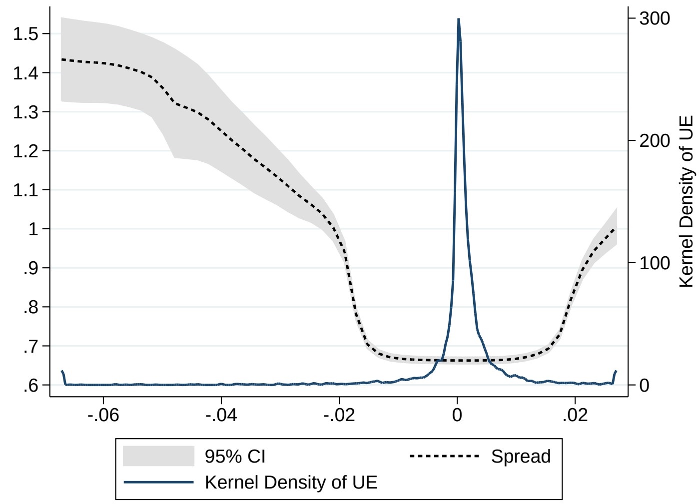
	6/10E	6/10A	Comments
Revenue	**$6,497,610**	**$6,566,000**	**1% above our estimate; +41% Y/Y (+42% ex. FX), vs. +14% in CQ2:09**
Media	2,923,100	2,874,000	
Electronics & Other General Merchandise	3,379,230	3,489,000	First time EGM revenue 50%+ of total revenue; +69% Y/Y
Other	195,280	203,000	
North America	$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)	**577,008**	**535,000**	
Net Interest (Income) and Other (Income)	(2,199)	(27,000)	
Pre-Tax Profit (excl. Stock Comp. & Other)	**$422,862**	**$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	**0.53**	**0.45**	**Below our estimate due to revenue higher-than-expencted opexl; taxes $0.04 negative impact to EPS.**

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

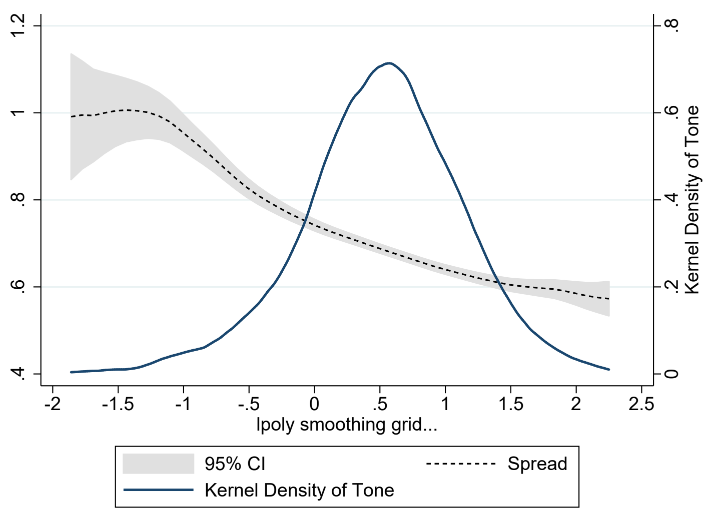
Tables and Figures

Figure 1: Analysts' Assessment of Future Risk and Valuation Uncertainty following Earnings Announcements.

(a) Local polynomial smooth of *Spread* on *UE*

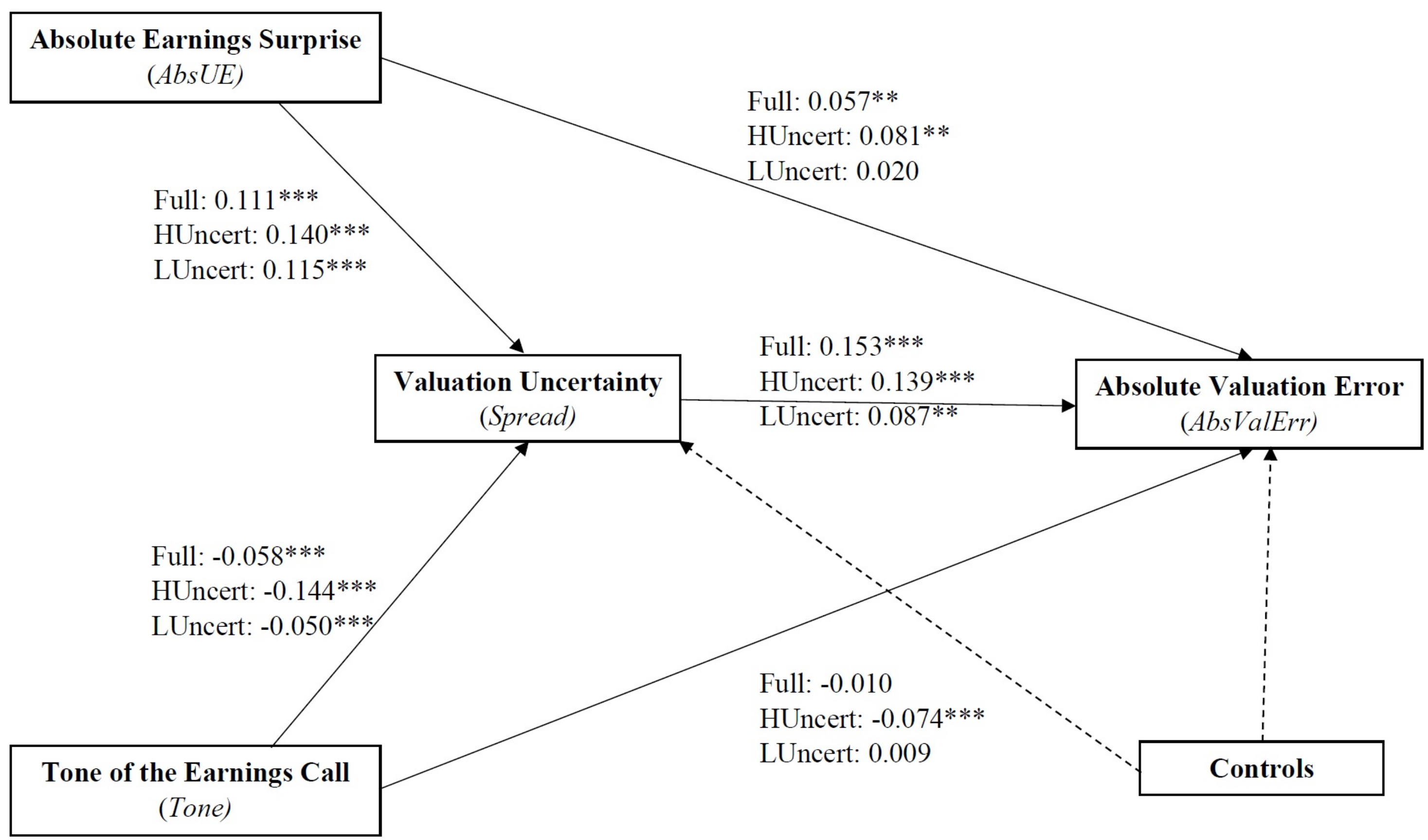


(b) Local polynomial smooth of *Spread* on *Tone*



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

Figure 2: Quantitative and Qualitative Information in Earnings Conference Calls, Valuation Uncertainty, and Valuation Error. Path Analysis.



This figure shows the standardized coefficients of the direct, indirect, and total effects between quantitative (*AbsUE*) and qualitative (*Tone*) variables in the earnings conference call and analysts' perceived valuation risk (*Spread*) and subsequent valuation error (*AbsValErr*). The analysis is performed using a structural equation model for the full sample (Full) and high and low macroeconomic uncertainty sub-samples (HUncert and LUncert). All variables are defined in Table A1. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively, using the Sobel test (Sobel, 1987). Number of observations: 4,286.

Table 1: Descriptive Statistics

	Mean	Median	STD	Q1	Q3
Panel A: Main Variables					
Spread	0.6914	0.6207	0.3076	0.4762	0.8333
BaseReturn	0.1546	0.1213	0.2807	0.0210	0.2394
Tilt	0.5476	0.5556	0.1304	0.4706	0.6364
AbsValErr	0.3511	0.2609	0.3183	0.1182	0.4856
UE	0.0002	0.0006	0.0096	−0.0001	0.0022
AbsUE	0.0040	0.0013	0.0087	0.0005	0.0035
GoodNews	0.6667	1.0000	0.4714	0.0000	1.0000
Tone	0.5061	0.5339	0.6147	0.1431	0.9062
ToneIntro	0.8855	0.9282	0.8969	0.3290	1.5053
ToneQA	0.2330	0.2533	0.5583	−0.1012	0.5906
Panel B: Control Variables					
Beta	1.2247	1.1670	0.5473	0.8516	1.5217
IdioRisk	0.5095	0.3914	1.0062	−0.1667	1.0355
Loss	0.1483	0.0000	0.3554	0.0000	0.0000
EarnVol	0.0191	0.0093	0.0283	0.0046	0.0204
FirmSize	9.0228	9.0235	1.4702	8.0399	9.9816
BTM	0.5223	0.3968	0.4673	0.2416	0.6726
Leverage	3.0974	1.4466	4.8147	0.6754	3.5126
NegBV	0.0235	0.0000	0.1516	0.0000	0.0000
VIX	25.6942	22.0780	11.7678	18.1660	27.5940
Observations	4,336				

Table 2: Correlation Table

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) *Spread*	1.00													
(2) *BaseReturn*	0.30***	1.00												
(3) *Tilt*	−0.21***	0.33***	1.00											
(4) *AbsValErr*	0.33***	0.24***	−0.12***	1.00										
(5) *UE*	−0.21***	−0.14***	0.08***	−0.12***	1.00									
(6) *AbsUE*	0.45***	0.18***	−0.16***	0.22***	−0.58***	1.00								
(7) *GoodNews*	−0.13***	−0.07***	0.08***	−0.06***	0.43***	−0.13***	1.00							
(8) *Tone*	−0.29***	−0.13***	0.12***	−0.14***	0.21***	−0.28***	0.21***	1.00						
(9) *Beta*	0.50***	0.14***	−0.09***	0.20***	−0.10***	0.34***	−0.07***	−0.22***	1.00					
(10) *IdioRisk*	0.02	0.00	−0.11***	0.13***	−0.00	0.05***	0.00	0.03*	−0.43***	1.00				
(11) *Loss*	0.40***	0.10***	−0.14***	0.18***	−0.10***	0.37***	−0.09***	−0.12***	0.33***	0.11***	1.00			
(12) *EarnVol*	0.22***	0.05***	−0.14***	0.12***	0.04***	0.11***	0.01	0.02	0.12***	0.15***	0.33***	1.00		
(13) *FirmSize*	−0.38***	0.01	0.27***	−0.20***	0.06***	−0.24***	0.08***	0.07***	−0.29***	−0.20***	−0.37***	−0.30***	1.00	
(14) *BTM*	0.28***	0.13***	0.02	0.07***	−0.19***	0.39***	−0.10***	−0.30***	0.41***	−0.17***	0.25***	−0.04***	−0.15***	1.00
(15) *Leverage*	0.13***	0.07***	0.03**	0.01	−0.09***	0.19***	−0.10***	−0.25***	0.25***	−0.13***	0.10***	−0.17***	0.08***	0.28***

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Analysts' Assessment of Future Risk and Valuation Uncertainty for High and Low Earnings Surprise
Terciles by High and Low Tone Terciles.

Panel A. Averages of Spread, UE, and Tone - Sort by Unexpected Earnings				
	Low UE	**Med UE**	**High UE**	**Low-High UE**
Spread	0.726	0.602	0.743	-0.017
				(-0.66)
Observations	[1,497]	[1,411]	[1,428]	
Panel B. Averages of Spread, UE, and Tone - Sort by Tone				
	Low Tone	**Med Tone**	**High Tone**	**Low-High Tone**
Spread	0.760	0.678	0.623	0.137***
				(6.83)
Observations	[1,473]	[1,436]	[1,427]	
Panel C. Averages of Spread - Two-way Sort by Unexpected Earnings and Tone				
	Low Tone	**Med Tone**	**High Tone**	**Low-High Tone**
Low UE	0.794	0.717	0.611	0.183***
	[651]	[498]	[348]	(6.56)
Med UE	0.639	0.612	0.572	0.067***
	[365]	[440]	[606]	(3.20)
High UE	0.808	0.727	0.696	0.112***
	[457]	[498]	[473]	(4.05)
Low-High UE	-0.014	-0.010	-0.085***	
	(-0.58)	(-0.47)	(-3.82)	

This table shows the average *Spread* for (1) high, medium and low 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 4: Analysts' Assessment of Future Risk and Valuation Uncertainty following Earnings Conference Calls.

		Spread	
AbsUE	4.172***		4.042***
	(6.30)		(6.05)
Tone		−0.034***	−0.030***
		(−4.28)	(−3.83)
GoodNews	−0.016**	−0.013*	−0.011
	(−2.29)	(−1.77)	(−1.55)
BaseReturn	0.187***	0.197***	0.184***
	(8.64)	(8.96)	(8.51)
Tilt	−0.245***	−0.260***	−0.232***
	(−5.36)	(−5.58)	(−5.11)
Beta	0.172***	0.180***	0.169***
	(11.58)	(12.05)	(11.37)
IdioRisk	0.049***	0.054***	0.048***
	(6.31)	(7.08)	(6.30)
Loss	0.077***	0.095***	0.079***
	(3.74)	(4.53)	(3.83)
EarnVol	0.328	0.334	0.312
	(1.37)	(1.40)	(1.29)
FirmSize	−0.018***	−0.018***	−0.018***
	(−4.21)	(−4.05)	(−4.23)
BTM	0.041***	0.060***	0.039***
	(2.83)	(3.91)	(2.71)
Leverage	0.005***	0.006***	0.005***
	(3.27)	(3.88)	(3.25)
NegBV	−0.027	−0.078	−0.042
	(−0.12)	(−0.38)	(−0.20)
BTM × *NegBV*	−0.938***	−1.073***	−0.946***
	(−3.27)	(−3.47)	(−3.28)
Leverage × *NegBV*	−0.013	−0.020	−0.014
	(−0.48)	(−0.79)	(−0.52)
Analyst FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Observations	4,336	4,336	4,336
Adj. R^2	0.649	0.643	0.651

This table shows the estimated coefficients from a regression of *Spread* on absolute earnings surprise (*UE*), tone of the earnings conference call (*Tone*) 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 the clustering at the firm level.

Table 5: Analysts' Assessment of Future Risk and Valuation Uncertainty for High and Low Macro-Uncertainty Periods.

Panel A. Averages of Spread, UE, Tone, VIX, and Crisis - Low and High VIX Periods

	Low VIX			**High VIX**			**Difference**
	Mean	Med	STD	Mean	Med	STD	High-Low
Spread	0.638	0.576	0.276	0.745	0.666	0.327	0.106^{***}
UE	0.0008	0.0006	0.007	-0.0003	0.0006	0.011	-0.001^{***}
AbsUE	0.003	0.001	0.007	0.005	0.002	0.010	0.002^{***}
Tone	0.618	0.619	0.575	0.393	0.428	0.632	-0.225^{***}
VIX	18.29	18.16	1.954	33.12	27.59	12.78	14.83^{***}
Crisis	0.125	0	0.331	0.506	1	0.500	0.381^{***}
Observations	2,172			2,164			

Panel B. Averages of Spread, UE, Tone, VIX, and Crisis - Crisis and No-Crisis Periods

	NoCrisis			**Crisis**			**Difference**
	Mean	Med	STD	Mean	Med	STD	Crisis-NoCrisis
Spread	0.655	0.590	0.282	0.768	0.697	0.343	0.113^{***}
UE	0.001	0.0007	0.007	-0.002	0.0004	0.013	-0.003^{***}
AbsUE	0.003	0.001	0.006	0.006	0.001	0.012	0.003^{***}
Tone	0.619	0.617	0.562	0.260	0.309	0.649	-0.359^{***}
VIX	21.01	19.51	4.832	35.83	29.13	15.41	14.82^{***}
Observations	2,967			1,369			

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows the average *Spread*, *UE*, *AbsUE* and *Tone* 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 macro-uncertainty; *Crisis*: high macro-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. Statistical significance is based on clustering at the firm level.

Table 6: Analysts' Assessment of Future Risk and Valuation Uncertainty following Earnings Conference Calls. Periods of High Macro-Uncertainty.

Panel A: Period of High Market Volatility			
HighVIX	0.049^{***}	0.078^{***}	0.069^{***}
	(6.36)	(7.68)	(5.88)
AbsUE	4.580^{***}		4.688^{***}
	(3.97)		(4.09)
AbsUE × *HighVIX*	1.121		0.172
	(0.96)		(0.14)
Tone		-0.027^{***}	-0.027^{***}
		(−2.95)	(−2.91)
Tone × *HighVIX*		-0.061^{***}	-0.048^{***}
		(−5.70)	(−3.96)
GoodNews	-0.019^{***}	-0.013^{*}	−0.010
	(−2.59)	(−1.69)	(−1.38)
BaseReturn	0.216^{***}	0.225^{***}	0.207^{***}
	(9.79)	(10.15)	(9.48)
Tilt	-0.282^{***}	-0.282^{***}	-0.247^{***}
	(−6.23)	(−6.02)	(−5.47)
Beta	0.142^{***}	0.152^{***}	0.140^{***}
	(9.79)	(10.33)	(9.57)
IdioRisk	0.021^{***}	0.026^{***}	0.020^{***}
	(3.20)	(4.01)	(3.12)
Loss	0.066^{***}	0.091^{***}	0.072^{***}
	(3.26)	(4.37)	(3.53)
EarnVol	0.373	0.388	0.359
	(1.52)	(1.56)	(1.42)
FirmSize	-0.027^{***}	-0.027^{***}	-0.027^{***}
	(−6.27)	(−6.08)	(−6.21)
BTM	0.063^{***}	0.084^{***}	0.059^{***}
	(4.32)	(5.47)	(4.10)
Leverage	0.006^{***}	0.006^{***}	0.005^{***}
	(3.72)	(4.28)	(3.59)
NegBV	−0.019	−0.085	−0.043
	(−0.09)	(−0.43)	(−0.21)
BTM × *NegBV*	-1.026^{***}	-1.180^{***}	-1.029^{***}
	(−3.67)	(−3.81)	(−3.60)
Leverage × *NegBV*	−0.013	−0.022	−0.015
	(−0.53)	(−0.94)	(−0.59)
Analyst FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	4,336	4,336	4,336
Adj. R^2	0.613	0.609	0.621

This table shows the estimated coefficients from a regression of *Spread* on absolute earnings surprise (*UE*), tone of the earnings conference call (*Tone*), their interaction with *HighVIX* (Panel A) and *Crisis* (Panel B) indicators and other controls. Analyst and industry fixed effects, and the constant are included in the regressions, but are not reported. High VIX period is identified relative to the sample median. Crisis period (of 2008-2009) is identified by NBER. 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 at the firm level.

Table 6: Analysts' Assessment of Future Risk and Valuation Uncertainty following Earnings Conference Calls. Periods of High Macro-Uncertainty.

Panel B: Period of Financial Crisis			
Crisis	0.061***	0.087***	0.070***
	(5.77)	(7.95)	(5.60)
AbsUE	3.936***		3.957***
	(3.51)		(3.54)
AbsUE × *Crisis*	1.871		0.932
	(1.44)		(0.68)
Tone		−0.028***	−0.030***
		(−3.20)	(−3.46)
Tone × *Crisis*		−0.074***	−0.052***
		(−6.26)	(−3.71)
GoodNews	−0.014*	−0.007	−0.005
	(−1.95)	(−0.96)	(−0.72)
BaseReturn	0.214***	0.225***	0.207***
	(9.95)	(10.37)	(9.66)
Tilt	−0.265***	−0.267***	−0.236***
	(−5.69)	(−5.59)	(−5.09)
Beta	0.142***	0.153***	0.141***
	(10.13)	(10.85)	(10.09)
IdioRisk	0.017**	0.023***	0.018***
	(2.54)	(3.55)	(2.73)
Loss	0.073***	0.096***	0.078***
	(3.54)	(4.63)	(3.80)
EarnVol	0.410*	0.387	0.369
	(1.65)	(1.53)	(1.45)
FirmSize	−0.028***	−0.027***	−0.027***
	(−6.57)	(−6.27)	(−6.39)
BTM	0.070***	0.092***	0.068***
	(4.75)	(5.97)	(4.58)
Leverage	0.006***	0.007***	0.006***
	(4.02)	(4.46)	(3.85)
NegBV	−0.035	−0.091	−0.056
	(−0.18)	(−0.48)	(−0.28)
BTM × *NegBV*	−1.094***	−1.213***	−1.086***
	(−3.87)	(−3.93)	(−3.74)
Leverage × *NegBV*	−0.016	−0.024	−0.017
	(−0.68)	(−1.06)	(−0.73)
Analyst FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	4,336	4,336	4,336
Adj. R^2	0.613	0.611	0.621

Table 7: Mapping of Qualitative and Quantitative Information into Spread and Absolute Valuation Errors.

Panel A: Full Sample		
Outcome Variable: *AbsValErr* **Mediating Variable:** *Spread*	Standardized Coefficient	Z-statistic
Direct Effects		
AbsUE	0.057**	2.10
Tone	−0.010	−0.53
Spread	0.153***	5.61
Mediating Path		
AbsUE, Spread	0.111***	5.94
Tone, Spread	−0.058***	−3.81
Indirect Effects		
AbsUE	0.017***	3.84
Tone	−0.009***	−3.17
Total Effects (Direct + Indirect)		
AbsUE	0.074***	2.67
Tone	−0.019	−0.98
Spread	0.153***	5.61
% Effect Mediated		
AbsUE, Spread	23.0%	
Tone, Spread	47.4%	
Controls	Yes	
Analyst, Industry, Year-Quarter FE	Yes	
Observations	4,286	
R^2	0.75	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This panel shows the standardized coefficients of a path analysis of the relations between quantitative (*AbsUE*) and qualitative (*Tone*) variables in the earnings conference call and analysts' perceived valuation risk (*Spread*) and subsequent valuation error (*AbsValErr*). We estimate a structural equation model to estimate the direct effects of *AbsUE* and *Tone* on *AbsValErr*, as well as the indirect effects of *AbsUE* and *Tone* on *AbsValErr* mediated by *Spread*. All control variables are same as in Table 4. All variables are defined in Table A1. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively, using the Sobel test (Sobel, 1987).

Table 7: Mapping of Qualitative and Quantitative Information into Spread and Absolute Valuation Errors.

Panel B: Periods of High and Low Macroeconomic Uncertainty.

	High Macro-Uncertainty		**Low Macro-Uncertainty**	
Outcome Variable: *AbsValErr* **Mediating Variable:** *Spread*	Standardized Coefficient	Z-statistic	Standardized Coefficient	Z-statistic
Direct Effects				
AbsUE	0.081**	2.50	0.020	0.51
Tone	−0.074***	−0.51	0.009	0.39
Spread	0.139***	3.79	0.087**	2.04
Mediating Path				
AbsUE, Spread	0.140***	6.30	0.115***	3.19
Tone, Spread	−0.144***	−6.84	−0.050***	−2.68
Indirect Effects				
AbsUE	0.020***	3.02	0.010*	1.67
Tone	−0.020***	−3.34	−0.004*	−1.66
Total Effects (Direct + Indirect)				
AbsUE	0.101***	2.95	0.030	0.79
Tone	−0.094***	−3.57	0.005	0.21
Spread	0.139***	3.79	0.087**	2.04
% Effect Mediated				
AbsUE, Spread	19.4%		33.3%	
Tone, Spread	21.2%		80.0%	
Controls	Yes		Yes	
Analyst, Industry FE	Yes		Yes	
Observations	2,411		1,875	
R^2	0.69		0.75	

This panel shows the standardized coefficients of a path analysis of the relations between quantitative (*AbsUE*) and qualitative (*Tone*) variables in the earnings conference call and analysts' perceived valuation risk (*Spread*) and subsequent valuation error (*AbsValErr*) in periods of high and low macroeconomic uncertainty (as indicated by *Crisis* or *High VIX* (relative to the sample median)). We estimate a structural equation model to estimate the direct effects of *AbsUE* and *Tone* on *AbsValErr*, as well as the indirect effects of *AbsUE* and *Tone* on *AbsValErr* mediated by *Spread*. All control variables are same as in Table 6. All variables are defined in Table A1. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively, using the Sobel test (Sobel, 1987).

Table 8: Positive and Negative Tone in Earnings Conference Calls.

	Spread		
AbsUE	4.114***	4.070***	4.033***
	(6.18)	(6.10)	(6.02)
PosTone	−0.030***		−0.025**
	(−2.77)		(−2.25)
NegTone		0.043***	0.038***
		(3.02)	(2.62)
GoodNews	−0.013*	−0.012*	−0.011
	(−1.93)	(−1.74)	(−1.51)
BaseReturn	0.185***	0.185***	0.184***
	(8.58)	(8.54)	(8.51)
Tilt	−0.240***	−0.234***	−0.231***
	(−5.24)	(−5.22)	(−5.13)
Beta	0.170***	0.171***	0.169***
	(11.50)	(11.39)	(11.33)
IdioRisk	0.048***	0.049***	0.048***
	(6.30)	(6.31)	(6.29)
Loss	0.079***	0.076***	0.078***
	(3.83)	(3.75)	(3.83)
EarnVol	0.319	0.319	0.312
	(1.33)	(1.31)	(1.28)
FirmSize	−0.018***	−0.019***	−0.019***
	(−4.07)	(−4.42)	(−4.27)
BTM	0.044***	0.035**	0.038**
	(3.01)	(2.30)	(2.49)
Leverage	0.005***	0.005***	0.005***
	(3.39)	(3.07)	(3.20)
NegBV	−0.039	−0.031	−0.041
	(−0.18)	(−0.14)	(−0.19)
BTM × *NegBV*	−0.955***	−0.924***	−0.940***
	(−3.29)	(−3.26)	(−3.27)
Leverage × *NegBV*	−0.014	−0.012	−0.014
	(−0.53)	(−0.46)	(−0.51)
Analyst FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Observations	4,336	4,336	4,336
Adj. R^2	0.650	0.650	0.650

This table shows the estimated coefficients from a regression of *Spread* on absolute earnings surprise (UE), positive and negative tone of the earnings conference call (*PosTone* and *NegTone*) 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 the clustering at the firm level.

Table 9: Extreme Tone in Earnings Conference Calls and Analysts' Assessment of Future Risk and Valuation Uncertainty.

		Spread	
AbsUE	4.160***	4.175***	4.163***
	(6.29)	(6.29)	(6.28)
ExtremeTone	−3.982***		−3.690**
	(−3.49)		(−2.21)
ModerateTone		−0.451	−0.227
		(−1.48)	(−0.71)
GoodNews	−0.012*	−0.015**	−0.012*
	(−1.78)	(−2.18)	(−1.76)
BaseReturn	0.186***	0.186***	0.186***
	(8.61)	(8.61)	(8.59)
Tilt	−0.239***	−0.245***	−0.239***
	(−5.28)	(−5.36)	(−5.28)
Beta	0.171***	0.172***	0.171***
	(11.55)	(11.60)	(11.56)
IdioRisk	0.049***	0.050***	0.049***
	(6.34)	(6.33)	(6.32)
Loss	0.078***	0.077***	0.078***
	(3.81)	(3.75)	(3.80)
EarnVol	0.327	0.323	0.325
	(1.36)	(1.35)	(1.35)
FirmSize	−0.017***	−0.018***	−0.017***
	(−3.93)	(−4.20)	(−3.94)
BTM	0.039***	0.041***	0.039***
	(2.69)	(2.77)	(2.67)
Leverage	0.005***	0.005***	0.005***
	(3.26)	(3.27)	(3.26)
NegBV	−0.040	−0.031	−0.042
	(−0.18)	(−0.14)	(−0.19)
BTM × *NegBV*	−0.939***	−0.936***	−0.938***
	(−3.33)	(−3.25)	(−3.31)
Leverage × *NegBV*	−0.014	−0.013	−0.014
	(−0.53)	(−0.50)	(−0.53)
Analyst FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
F-test of *Extreme* = *Moderate*			3.91++
Observations	4,336	4,336	4,336
Adj. R^2	0.649	0.649	0.649

This table shows the estimated coefficients from a regression of *Spread* on absolute earnings surprise (*UE*), extreme and moderate tone of the earnings conference call (*ExtremeTone* and *ModerateTone*) 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 the clustering at the firm level.

Table 10: Introduction and Questions and Answers Sections of Earnings Calls.

AbsUE	4.047***	4.122***	4.038***	3.935***
	(6.07)	(6.18)	(6.03)	(5.79)
ToneIntro	−0.020***		−0.022***	−0.022***
	(−3.63)		(−3.92)	(−3.93)
ToneQA		−0.025***		
		(−3.49)		
$ToneQA^{\perp}$			−0.016**	
			(−2.10)	
$ExecToneQA^{\perp}$				−0.015**
				(−2.10)
$AnaToneQA^{\perp}$				−0.013**
				(−2.15)
GoodNews	−0.011	−0.012*	−0.010	−0.012*
	(−1.64)	(−1.80)	(−1.46)	(−1.73)
BaseReturn	0.184***	0.185***	0.183***	0.184***
	(8.49)	(8.59)	(8.48)	(8.30)
Tilt	−0.234***	−0.237***	−0.231***	−0.235***
	(−5.12)	(−5.21)	(−5.07)	(−5.04)
Beta	0.170***	0.170***	0.169***	0.168***
	(11.36)	(11.53)	(11.37)	(11.23)
IdioRisk	0.048***	0.049***	0.048***	0.049***
	(6.29)	(6.33)	(6.31)	(6.31)
Loss	0.079***	0.078***	0.079***	0.074***
	(3.84)	(3.78)	(3.84)	(3.59)
EarnVol	0.307	0.321	0.306	0.327
	(1.25)	(1.34)	(1.25)	(1.33)
FirmSize	−0.018***	−0.018***	−0.018***	−0.018***
	(−4.18)	(−4.26)	(−4.22)	(−4.10)
BTM	0.038***	0.040***	0.038***	0.039***
	(2.63)	(2.74)	(2.61)	(2.64)
Leverage	0.005***	0.005***	0.005***	0.005***
	(3.25)	(3.24)	(3.23)	(3.12)
NegBV	−0.046	−0.034	−0.047	−0.050
	(−0.21)	(−0.16)	(−0.21)	(−0.22)
BTM × *NegBV*	−0.941***	−0.941***	−0.943***	−0.968***
	(−3.32)	(−3.23)	(−3.28)	(−3.26)
Leverage × *NegBV*	−0.014	−0.013	−0.014	−0.014
	(−0.53)	(−0.49)	(−0.53)	(−0.47)
Analyst FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	4,336	4,336	4,336	4,230
Adj. R^2	0.651	0.650	0.651	0.650

This table shows the estimated coefficients from a regression of *Spread* on absolute earnings surprise (*UE*), tone of the introductory remarks and Q&A sections in the earnings conference call (*ToneIntro* and *ToneQA*) and other controls. $^{\perp}$ indicates that the Q&A tone measure is orthogonalized with respect to *ToneIntro*. 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 at the firm level.