The Power of Voice:
Managerial Affective States and Future Firm Performance

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Abstract: In this study, we measure managerial affective states during earnings conference calls by analyzing conference call audio files using vocal emotion analysis software. We hypothesize and find that when managers are scrutinized by analysts during conference calls, positive and negative affect displayed by managers are informative about the firm's financial future. In particular, we find that managers exhibiting positive (negative) affect are positively (negatively) related to contemporaneous stock returns and future unexpected earnings. However, analysts do not incorporate the information when determining short term earnings forecasts. When making stock recommendation changes, however, analysts incorporate positive affect but not negative affect. We observe market underreaction to negative affect as if market participants follow analyst recommendation changes. Together, this study presents new evidence that managerial vocal cues contain useful information about firms' fundamentals, incremental to both quantitative earnings information and qualitative "soft" information conveyed by the linguistic content.

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“It is not what you say that matters but the manner in which you say it; there lies the secret of the ages.”

- William Carlos Williams

Managers disseminate an inordinate amount of quantitative and qualitative information about their actions and firm performance on a voluntary and mandatory basis through several avenues such as press releases, quarterly and annual reports, and earnings conference calls. Prior literature is replete with studies that evaluate the extent that capital market participants react to quantitative information contained in such disclosures. Only recently have researchers begun to explore the capital market implications of qualitative verbal communication via financial news stories (Tetlock, 2007; Tetlock, Saar-Tsechansky, and Macskassy, 2008), annual reports (Li, 2006; Loughran and McDonald 2009) conference presentations (Bushee, Jung and Miller 2007), and earnings press releases (Davis, Piger, and Sedor, 2007; Demers and Vega, 2007). In general, the findings support the hypothesis that qualitative verbal communication by managers is incrementally useful to quantitative information in predicting future firm fundamentals and stock returns. This paper extends this line of inquiry by focusing on how one important type of nonverbal communication, vocal cues from executives during conference calls, can inform about a firms’ future profitability and stock returns.

Using a sample of conference call audio files and proprietary Layered Voice Analysis (LVA) software, we analyze managerial vocal cues to measure positive and negative dimensions of a manager’s affective or emotional state. Research in linguistics and social psychology has long recognized that human voice conveys considerable information over and above the literal meaning contained in verbal content (Caffi and Janney, 1994). Vocal cues or expressions are considered to be important in drawing inferences about both positive affective states (e.g., happiness, excitement, and enjoyment) and negative affective states (anger, fear, sadness, tension, and anxiety). The appraisal theory of emotion suggests that affective states arise from an individual’s cognitive evaluation of a situation or stimulus and its attendant implications for personal well-being. In other words, affective states are responses to interpretation and evaluation of events and stimuli and hence reveal useful information. The extent of the emotional response will be a function of the strength of the stimulus or elicitor.

In the context of conference calls, the external stimulus that is likely to produce affective states is the questioning by analysts during the conference call. More importantly, the affective state is likely to be more prominent when the analysts' questions are more pointed and scrutinizing during the conference calls. Consequently, affective states elicited from analysts' probing during the conference call are likely to contain useful information about the firm's economic activities and performance. Recent survey evidence by Graham, Harvey and Rajgopal (2005) suggest that managers who miss analysts' earnings expectations face extensive questioning during the conference calls. We therefore posit that affective states are most likely to be elicited during the question and answer portion of the conference call, and in particular, when firms have missed earnings expectations and are subject to intense scrutiny by analysts.

To the extent that the affective states exhibited by managers during conference calls represent new information about firm fundamentals we hypothesize that investors should incorporate them into stock prices. Consistent with this prediction, we find that both positive and negative affect exhibited by managers during the question and answer portion of earnings conference calls are associated with contemporaneous stock returns even after controlling for the linguistic content in the conference calls. Moreover, the stock market's response to the information contained in the affective state is more pronounced when managers are "interrogated" and subject to more scrutiny during the conference calls.

While investors react to affective states as if they carry value relevant information, analysts do not react in a similar fashion when determining their near term earnings forecasts. That is, we are unable to document a relation between affective states and forecast revisions of one period ahead earnings following the conference call. This result is open to two interpretations. Either analysts fail to appreciate the value implications of nonverbal cues or analysts do consider the information but incorporate it as part of the "soft" information in determining long term forecasts that underpin stock recommendations. Our evidence is consistent with the latter interpretation. We find a positive association between positive affect and changes in stock recommendations immediately following the call. However, we find no association between negative affect and recommendation changes, consistent with analyst incentives to delay incorporating bad news into their stock recommendations (O'Brien et al., 2005).

Next, we examine whether the stock market reaction around the earnings call is consistent with future firm-specific information about fundamentals. We find that both positive and negative affect are associated with future unexpected earnings (based on analyst expectations) measured over the two subsequent quarters. This evidence is consistent with the capital market response surrounding the conference call. Moreover, it is also consistent with analysts failing to incorporate the information contained in vocal cues into near term forecasts.

In addition to hard fundamental information such as earnings, we also examine firm issued press releases from news wires for 180 days following the conference call. We classify news releases as good (bad) depending on the market reaction surrounding the press release and compute the proportion of bad news releases following the call. Our findings suggest that managers that exhibit positive affect are associated with a lower proportion of bad news press releases in the future.

Finally, we examine whether market participants reflect managerial affect for future performance with any delay. We find that negative affect is related to cumulative abnormal returns over the subsequent 180 trading days following the earnings conference call. We cannot identify for certain why market participants fail to fully incorporate negative affect. However, one plausible explanation is consistent with our findings relating to analyst recommendation changes following the conference call. Recall that we find evidence that analysts incorporate positive affect but not negative affect into their recommendations. If part of the contemporaneous market response results from analyst recommendation changes, the lack of downgrading for negative affect would imply a less than complete market reaction to negative affect. Regardless, we caution the reader that although this apparent under reaction by market participants to negative affect points to a plausible trading strategy, transaction costs could eliminate any potential trading profits.

This study makes three contributions. First, to our knowledge, this is the first paper to provide evidence on the role of nonverbal communication in a capital market setting. We apply findings in social psychology research that provide unequivocal support for vocal expressions as one particular type of nonverbal communication that is influential when communicating messages over and above the verbal content of message (Mehrabian and Weiner, 1967; Scherer, London, and Wolf, 1973; Scherer, 2003). Our findings confirm that important information can be gleaned from vocal cues in the capital market setting by showing that managers' emotional state is associated with stock returns and future firm performance, after controlling for quantitative information and qualitative verbal content. Our results are also robust to manager characteristics such as CEO's age and tenure that could potentially influence the extent of emotions exhibited by the manager.

Second, our results provide new insights into how conference calls can provide information to financial markets. Prior research documents that conference calls provide significant information to market participants above and beyond that contained in the earnings press release (e.g. Frankel, Johnson, and Skinner, 1999; Tasker, 1998; Bushee, Matsumoto, and Miller, 2004). As conference call audio broadcasts are commonplace for many firms and open to public access subsequent to Regulation FD, our findings suggest that investors can and do utilize vocal cues during such communication to learn about a manager's affective state, and in turn about the firm's financial future.

Finally, we exploit a new tool that can potentially help researchers measure emotional states. Our results provide preliminary evidence that the LVA software can produce useful and reliable proxies for managerial affect in the capital market setting. Future research in both economics and psychology can explore vocal cues using this software in other settings. For example, examining information about the affective states of economic leaders can perhaps inform about broader changes in economic fundamentals. For psychology researchers who rely on human subjects to observe and measure affect from voice, this represents a useful and feasible alternative. Certainly more empirical validation of this software's reliability is necessary, but we view our results along with recent findings in Hobson et al. (2009) as encouraging.

Our paper proceeds as follows. In Section I we review related literature and develop our hypotheses. Section II discusses the nonverbal measures used in the study. In section III we outline our sample selection, define our variables of interest, and provide descriptive statistics. Sections IV and V discusses our empirical results and additional analyses, and in Section VI we offer concluding remarks.

I. Related Research and Hypotheses Development

A. Related Research

Research in social psychology has long held the view that nonverbal cues such as vocal and facial expressions significantly impact how a message is interpreted. Communication experts generally agree that in face-to-face conversations, only a small fraction of the message regarding emotional state is contained in the verbal content (e.g., Mehrabian, 1971). A significant component of the message is contained in vocal attributes such as voice intonation, accent, speed, volume, and inflection. Kinesics, i.e., facial expressions, postures, and gestures, also plays a large role in communication. However, we do not study them in this paper and will therefore not elaborate further on the role of kinesics. We will focus on the vocal channel and describe how voice can convey emotions or affective states reliably to a receiver (see for example Juslin and Laukka, 2003).[1]

The expression and perception of emotional states via vocal cues are fundamental aspects of human communication. People express emotions by yelling; using a quiet, low or monotonous voice; and at the extreme, by being silent (e.g., Walbott et al., 1986). Such expression of emotions through voice can be used to convey information or influence others. Several studies have shown that the tone of a person's voice leaks information about an affective state that is not revealed by the verbal content or facial expressions associated with the message (Zuckerman et al., 1982). Juslin and Scherer (2005) review fifty years of research establishing that acoustic voice patterns provide insights into the speakers affective, or emotional, state. While the role of nonverbal cues has been studied extensively in the social psychology literature, it is virtually absent from the accounting and finance literatures.

Corporate financial reporting represents an important channel for managers to communicate information to various stakeholders and much of the literature has primarily focused on the capital market

[1] Although we use the terms affect and emotion interchangeably, there is a subtle but important difference between the two. Emotion refers to a feeling that occurs in response to events, while affect is viewed as valence of an emotional state (Frijda, 1993).

implications of quantitative information disclosed in the financial statements. Recently, researchers have begun to explore verbal communication as an additional mechanism through which information is conveyed and used in capital markets. For example, the role of verbal communication has been examined in the context of financial news stories (Tetlock, 2007; Tetlock et al., 2008) and messages in Internet chat rooms (Antweiler and Frank, 2004). Using the General Inquirer textual analysis software, Tetlock (2007) examines whether pessimism in news media language content can predict movements in market returns. He finds that pessimism in the Wall Street Journal "Abreast of the Market" column exerts significant downward pressure on aggregate market valuations—but, such pessimism reverts quickly and has no implications for aggregate fundamentals. Building on Tetlock (2007), Tetlock et al. (2008) measure the pessimism in financial news stories for a sample of S&P 500 firms and find that pessimism predicts lower future firm earnings and stock returns.

Antweiler and Frank (2004) examine whether messages communicated through Internet message boards such as Yahoo! Finance have predictive ability for subsequent stock returns, trading volume, and volatility. They report that an increase in message board activity results in subsequent negative returns, greater trading volume, and return volatility. This evidence is consistent with Internet message boards conveying financially relevant information.

In the accounting literature, Davis et al. (2007) and Demers and Vega (2007) analyze the linguistic style of managers' language use in earnings press releases. They employ computerized textual-analysis software, DICTION 5.0, to measure the extent that managers exhibit optimism or pessimism in their language use. Collectively, they find that the levels of optimistic and pessimistic language in earnings press releases predict future performance and correlate significantly with contemporaneous market reaction surrounding the press release. Both Li (2006) and Loughran and McDonald (2009) examine the information content of textual information in annual reports.[2] Li (2009) develops a linguistic-based risk-sentiment measure by using words in the annual report and demonstrates that this risk-

[2] In the management literature, Bettman and Weitz (1983) explore the linguistic content in annual reports to examine how managers explain firm outcomes. However, they do not examine investor reactions to managers' attributions. They find that managers attribute unfavorable outcomes to external and uncontrollable causes.

sentiment measure predicts both future earnings and returns. Loughran and McDonald (2009) refine the General Inquirer dictionaries and examine word associations with various market outcomes including stock returns, trading volume, trading volatility, fraud, material weakness disclosures and unexpected earnings.

Another avenue for managers to communicate information is via presentations at various conferences. Research by Bushee et al. (2007) shows that conference presentations are economically important information events in that they find significant short-window market reaction surrounding the conference date. In addition, they find that such conference presentations increase analyst and investor following consistent with the notion that firms use these venues to improve firm visibility and generate investor following.

While a growing body of literature explores the role of verbal communication in the financial markets arena, the implications of nonverbal communication represent a fairly nascent and unchartered territory. One exception is Coval and Shumway (2001) who examine the role of ambient noise level in the Chicago Board of Trade's bond future trading pit. They find that ambient sound level conveys economically and statistically meaningful information and that traders process subtle and complex nontransaction signals in determining equilibrium prices. While this suggests that decibel levels in trading pits have information content for equilibrium supply-and-demand conditions in the futures market, it does not speak directly to the specific attributes of nonverbal communication between managers and market participants that we address in our study.

B. Hypotheses

The affective or emotional state of an individual enables us to draw inferences about the events or type of events that caused an individual to be in such an emotional state. This is based on the appraisal theory of emotion that is founded on the notion that emotions arise or are elicited by evaluations or appraisals of events and situations (Arnold, 1960; Roseman, 1984; Lazarus, 1991). For example, a positive state is elicited by a successful outcome such as winning a basketball game, passing an exam, or being selected to a University. In contrast, a negative state is elicited by personal loss, frustration, cognitive dissonance or simply a bad outcome. Frijda (1988) calls it the Laws of Situational Meaning and Concern and states that "emotions arise in response to the meaning structures of given situations; . . . arise in response to events that are important to the individual's goals, motives, and concerns." In other word, emotions arise from an individual's cognitive evaluation and interpretation of events and situations that in turn has implications for personal well-being.

While human emotions can arise without an external stimulus, most of the emotions are the result of social and interpersonal communication (Andersen and Guerrero, 1998). The triggering event can be external (e.g., a loud noise) or internal (e.g., physiological change). External elicitors invoke cognitive processes that in turn trigger certain affective states. Most extant research in psychology focuses on external stimuli due to the difficulties in identifying internal elicitors that trigger affective states (Lewis, 1993). In order for an emotional state to arise some event acts as a stimulus that in turn triggers a change in the state of the individual.

In the context of financial markets, where managers communicate information to investors about both past and future performance, it is likely that managers exhibit different affective states depending on their interpretation of events and situations pertaining to the firm. Such affective states are most likely elicited when managers answer analyst questions. The determination of managerial affective states should enable investors infer the managers' implicit assessment of firm performance, both past and future. For example, a manager is likely to exhibit positive affective state during analyst questioning if the manager expects positive future firm performance due to private information regarding current outcomes (e.g., persistence of current period earnings) and/or future outcomes (e.g., prospective drug approval, anticipated orders, successful outcome of strategic initiatives such as restructuring). In such instances, a manager is more likely to be excited or exhibit positive psychological arousal in communication with investors.[3]

[3] We assume that a manager's affective state is not an innate characteristic of the manager per se. Rather, it is time-dependent and is a function of private information about the firm that managers possess during the conference call. It is plausible that a manager could exhibit both positive and negative affective states during the conference call if the manager has both good news and bad news about specific issues discussed during the conference call. For

In contrast, a manager may exhibit negative affective state when he/she has private information that is not indicative of positive future performance. Examples include information about the transitory nature of accounting earnings, impending law suits, product failures or order cancellations. Negative affect may also stem from managers' psychological discomfort due to cognitive dissonance. The theory of cognitive dissonance, developed by Festinger (1957), is based on the notion that inconsistency between an individual's beliefs and their actions creates a feeling of discomfort and anxiety. In experiments conducted by Elliot and Devine (1994) counterattitudinal behavior evoked psychological discomfort arousing a negatively valenced state (see also Harmon-Jones 2000).

To apply cognitive dissonance in the economic setting we explore here, consider a manager who believes that she is competent and in control of the firm she operates. Information about firm performance would reflect her actions taken while running the firm. If the manager has private information that is inconsistent with her own beliefs regarding her competence, an uncomfortable emotional state will arise from this dissonance. As such, we posit that cognitive dissonance induced negative affect should be indicative of potential bad news or uncertainty about good news. Therefore, if we observe a manager in a negative affective state, it is more likely that events and circumstances are unfavorable and/or that the manger is psychologically uncomfortable due to cognitive conflicts in elements of information that the manager has.[4] Thus, we posit that negative affect will be negatively related to future firm performance.

If positive (negative) managerial affect is reflective of favorable (unfavorable) private information, we should observe a market reaction surrounding the communication date in a manner

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example, a manager may discuss poor past performance in the form of negative earnings surprise and at the same time discuss better expected future performance as a result of increasing backlog of orders.

[4] Our study attempts to measure the negative affect resulting from cognitive dissonance. Other research has investigated how individuals in economic settings take action to avoid cognitive dissonance *ex ante*. Akerlof and Dickens (1982) formally model cognitive dissonance costs as part of expected utility maximization and discuss how workers in dangerous occupations take actions to avoid reminders of how dangerous their work is. Argentesi, Lutkepohl and Motta (2007) show that individual investors (who believe they are competent investors) are more likely to avoid buying newspapers when their holdings have likely experienced losses because reading the paper would confirm unfavorable news would cause dissonance. Prentice (2003) notes that Enron repeatedly rebuked critics, making it difficult for its employees to process any negative information about the firm. In relying on management, employee beliefs were that the firm was in fine financial shape, and employees in turn would not process information to the contrary to avoid dissonance costs.

consistent with the signal contained in each of those cues. We therefore hypothesize a positive (negative) contemporaneous stock market response to positive (negative) affect.

Observing such a market reaction is contingent on i) the strength of the stimulus that generates the affective state, i.e., intensity of probing by analysts during the conference call and ii) the efficiency with which market participants observe and act on the information contained in the affective state. Research in social psychology suggests that vocal indicators of various emotions are accurately detected and are often as good as or better than those of facial cues and expressions (Kappas, Hess, and Scherer, 1991). It is also widely accepted that one's voice is not easily controlled and that the voice channel "leaks" more information than facial cues (Ekman and Friesen, 1974). Evidence in Ambady and Rosenthal (1993) suggests that human beings can form impressions and judgments from even "thin slices" of nonverbal behavior. However, the strength of any relation between affect and contemporaneous stock returns is also subject to the information processing efficiency and ability of market participants as well as measurement error in the nonverbal measures.

II. Measuring Nonverbal Communication

The main challenge in this study is to construct useful and reliable measures of affective states from nonverbal communication. We utilize CEO and CFO voice recordings from earnings conference calls to develop measures of managers' emotive states when communicating information to analysts and investors.[5]

There are several advantages to using the audio content in earnings conference calls. First, conference calls represent a common and important disclosure mechanism for U.S. firms. They are intended to supplement mandated disclosure of earnings information and, in particular, help analysts understand the implications of specific events or items reported in the earnings press release. Early research in the area (Frankel et al., 1999; Tasker, 1998) demonstrated that conference calls provide

[5] In the psychology literature, nonverbal cues are often generated by using actors to produce vocal emotion expressions, and human judges are used as "decoders" to determine whether such vocal patterns are recognized. While professional actors can provide strong vocal cues and it is easy to get consistent audio recordings, their emotional portrayals may differ from vocal expressions that occur in real life.

material information to analysts in particular, and to investors, more generally. The passage of Regulation FD has not diminished the role of conference calls (Bushee, Matsumoto, and Miller, 2004), and in fact most public firms regularly host quarterly earnings conference calls to comply with Regulation FD (Skinner, 2003). Recent research explores the implications of differences in the nature of conference calls, in terms of the amount of time allocated by firms for the conference call (Frankel, Mayew and Sun 2009), the linguistic tone (Matsumoto et al., 2007; Frankel et al. 2009), the interactions between the presentation and discussion portions of the call (Matsumoto et al., 2007), and management discrimination in allowing analysts to ask questions (Mayew, 2008). Together, these studies suggest conference calls are important venues for managerial communication with stakeholders of the firm. We extend this literature by examining whether vocal cues from managers during conference calls add incrementally to the quantitative and qualitative linguistic information already provided in the earnings conference call, as suggested by Block (2000).[6]

A second advantage of using conference calls is that, unlike annual meetings where managers appear face-to-face to meet with current investors, conference calls offer one of the few opportunities for firms to communicate directly with current and potential investors as well as other stakeholders. Third, because conference calls are rarely broadcast over video, other channels of nonverbal communication such as facial expressions and gestures (kinesics) do not contaminate the signal in the voice channel. In other words, we are able to isolate the vocal channel of the nonverbal communication.[7] Additionally, vocal expressions have been shown to be more effective than facial expressions over long distances (Marler, 1977), which is certainly the case with conference calls where analysts and investors are often

[6] An inherent assumption in prior research (e.g., Davis et al. 2007) that examines linguistic content in press releases is that managers use linguistic style in press releases and conference calls truthfully. It is unclear what the relative cost-benefits tradeoffs are for managers to engage in truthful revelation versus opportunistically manipulating the market via optimistic and pessimistic tone in earnings press releases. In contrast, our paper does not rely on the assumption of truthfulness on the part of managers. Rather, the vocal measures that we use capture both voluntary and involuntary aspects of communication and hence are less likely to be influenced by opportunistic manipulation of information. To the extent that managers are able to portray emotions to obfuscate information, we would bias our tests against finding results in support of the predictions.

[7] Note that the message recipient may react to the verbal or linguistic aspect of the communication in addition to or in lieu of the nonverbal content. We control for this possibility by including linguistic tone in the empirical analysis.

many miles away from the managers. Lastly, as a practical matter, we were able to obtain audio files of the conference calls from the Thomas Financial StreetEvents database.

We first considered using human judges to interpret emotive states in the managerial communication during conference calls. The use of human judges to interpret emotion expressions is a difficult and complex procedure, mainly due to the difficulties with an appropriate judge selection procedure and the lack of reliable inferences on judgments made by them. The use of sophisticated computer-aided analysis of emotional expressions has been steadily increasing in recent years. However, acoustic measurement brings with it its own set of problems. The sound recording quality is very crucial because the success of the acoustic measurement depends critically on the recording quality. Furthermore, translating the vocal cues, such as the fundamental frequency or voice pitch, voice intensity, voice quality, and temporal aspects of speech into specific measures that capture emotive states is nontrivial.

We construct measures of affective states with the help of a computer software program that uses Layered Voice Analysis Technology (LVA) developed by Nemesysco Ltd. LVA was invented in Israel in 1997. LVA is comprised of a set of unique proprietary signal processing algorithms that identify different types of stress, cognitive processes, and emotional reactions. The software algorithms internally use 129 vocal parameters to detect and measure minute and purportedly involuntary changes in various aspects of the speech waveform to enable a better understanding of a subject's mental state and emotional makeup during the time that he or she is speaking.

While the inner workings of LVA are proprietary, the software performs analysis and provides output at the voice segment level. A voice segment is a logical portion of continuous voice (a word to few words) that may range in length from 4/10th of a second to 2 seconds. The original objective of the software was to measure several different emotions that in different combinations likely underpin different types of lies (derived from different motivations). Combining the individual emotion parameters would then enable a user to conclude as to whether a speech segment was truthful (low risk) or should be suspected as deceptive (high risk). To that end, the software provides various layers of output, with the base layer being the building blocks of the emotion metrics produced by the software.

The base layer variables (technically termed as SPT, SPJ, JQ and AVJ) are raw values of the LVA Real Time (Online) analysis obtained from the voice wave. In addition to the raw values a set of parallel base-line values (calSPT, calSPJ, calJQ, calAVJ) are captured in what is assumed to be an "emotion free" or a period of time that reflects the general emotional state of the tested subject without relation to any specific detail, typically, at the beginning of the conversation. Differencing off the subject specific calibrated value of each raw base layer variable provides the four fundamental variables of LVA: Emotional Stress, Cognitive Stress, Global Stress and Thinking Stress. Adjusting for base-line values is of critical importance in the LVA analysis so that the system can take into account different emotional states, different personality structures, as well as some acoustic issues and audio quality. Emotional stress purports to capture excitement. Cognitive stress purports to capture cognitive dissonance. Global stress purports to capture overall physical negative arousal and fear, and Thinking stress purports to capture the mental effort behind what the subject is saying.

In addition to the fundamental variables produced by LVA, the software also provides "conclusion" variables (also known as algorithmic values) which are proprietary combinations (and typically generated using an automatically generated proprietary formula) of the four fundamental variables and base layer variables. These conclusion variables (e.g., Lie Stress or SOS) are meant to allow a user to draw conclusions about whether a given speech segment should be further examined or treated as potentially untruthful**.** For example, Lie stress reveals how different a voice segment is from the complete baseline in more than one array of emotions - and is made to raise suspicion whether the voice segment is untruthful relative to other portions of the subject's narrative**.**

The LVA technology underpins various software products for commercial and entertainment purposes (see www.nemesysco.com/solutions.html for a complete list) and depending on the particular software application, the number of base layers, fundamental output variables and conclusion variables provided to the end user varies. For example, LVA 6.50 (http://www.lva650.com/) is the security level version of the software used for police interrogations and military operations, and provides all metrics for all speech segments. Ex-Sense Pro - R (http://www.ex-sense.com/proversion.html) is marketed for business solutions such as interviewing customers, employees and potential business partners and provides users with graphical output at the segment level of all four first level variables, one second level variable and one third level variable at the segment level. StressIndicator (http://www.stressindicator.com/) is marketed for managing stress in daily life as a healthcare application and provides only a ranking of the first level parameter Global stress.

Deciding which software to employ (whether from Nemesysco or otherwise) requires a careful cost benefit analysis on many dimensions. The trade-offs we considered were the parameters provided by the software, the monetary cost of the software and finally the construct validity of the parameters. We decided to employ LVA based technology instead of other voice stress analyzers (such as Psychological Stress Evaluator (PSE) or Computerized Voice Stress Analysis (CVSA)) primarily for two reasons. First, some of these softwares required enormous capital investments for computers/software and second, they offered only basic diagnostics of true or false outcomes without providing basic emotion variables that capture positive and negative emotions. Furthermore, our objective is not to determine truth telling by company executives because it is not possible to identify "ground truth" in our setting. Rather, we are interested in capturing underlying emotional state that can be characterized as positive and negative. Therefore, we chose the LVA technology.

Conditional on using LVA technology, the next choice became which LVA technology to use. Because we are studying business communications, we initially felt the Ex-Sense Pro-R software was best suited for our purposes. Naturally, LVA 6.50 is a product that would subsume Ex-Sense Pro-R, but was much more expensive at over $14,500 per unit with training costs. Since our objective was to measure emotions on pre-existing executive conference call recordings as opposed to interrogation, and since Ex-Sense Pro-R provided the fundamental emotion variables that are most pertinent to our study, we decided it was optimal to use Ex-Sense Pro-R.

Regarding the construct validity of LVA metrics we summarize the literature that has examined LVA performance.[8] Because the software was originally designed to detect deception, numerous studies obtained voice samples from truth tellers and liars in experiments or field studies and examined whether LVA determined "conclusion" variables could distinguish between truth tellers and liars. Some studies conclude that LVA metrics perform no better than chance levels at detecting deception (Brown et al. 2003; Damphousse et al. 2007; Sommers et al. 2007; Sommers 2006; Harnsberger et al. 2009; Harnsberger and Hollien 2006). However, recent research by Adler (2009) tests the software in the sex offender setting where polygraphs are established tools for detecting deception, and finds that LVA third level variables perform as well as polygraphs. Consistent with this result, Heddad et al. (2002) compare LVA "conclusion" metrics of 48 voice segments from interrogation interviews of two murder suspects that were eventually convicted. In each case LVA summary metrics correctly identified existence of ground truth, where ground truth was established from polygraphs examiners and court proceedings.

That the results are mixed on a one-size-fit all summary measure of deception is perhaps not surprising. While research suggests that emotional profiles for those lying will be different from truth tellers, the precise combination of emotions that will be applicable in all settings is not known. Consistent with this notion, Damphousse et al. (2007) perform exploratory logistic regression analysis on predicting deception in their sample as a function of LVA base level variables instead of the conclusion variables. They find that detection capabilities are greatly improved using more primitive LVA variables.

Subsequent research has investigated more primitive LVA variables. Harnsberger et al. (2009) investigate the LVA base level JQ parameter, which is purported to capture global stress, is higher in settings where electric shocks were administered during speaking versus settings where no such shock was administered. In a different setting, Salganik et al. (2006) also examines whether JQ is higher in settings where tasks are more difficult, and finds corroborating evidence. Hobson et al. (2009) conduct an experiment where they induce subjects to misreport that in turn generates cognitive dissonance in the

[8] A detailed summary of the individual studies is available from the following website: http://faculty.fuqua.duke.edu/~wmayew/Bio/Data.htm.

subjects. They document strong association between those participants subject to cognitive dissonance and the LVA fundamental output variable, cognitive stress.

Given our choice of Ex-Sense Pro R, we then selected the two measures implicit in the LVA fundamental variables that are relevant for operationalizing positive and negative managerial affect.[9] The first measure, cognition level (cognitive stress in LVA), measures the level of cognitive dissonance (Festinger, 1957), which is a determinant of negative affective state (Forgas, 2001). Cognitive dissonance is the uncomfortable, anxious feeling an individual experiences when beliefs and actions are contradictory. Cognition level is a number based on low vocal frequency parameters that capture cognitive conflicts and general cognitive activity. This indicator takes on values ranging from 30% to 300%. Values above 120% indicate increasing doubt in the mind of the subject when speaking. Thus, the higher the cognition level, the greater the subject's cognitive conflict, and hence, the larger the negative affect (hereafter, *NAFF*).

The second measure, emotion level (emotional stress in LVA), measures the level of excitement exhibited by the subject. Excitement is one of the biological expressions that accompanies a positive affective state (Tomkins, 1962). As with cognition level, emotion level values range from 30% to 300%. Emotional levels greater than 110% indicate rising levels of excitement. Thus, the higher the emotion level, the larger the positive affect (hereafter, *PAFF*).[10]

Aside from Hobson et al. (2009) no existing research examines the fundamental LVA metrics we utilize, making it difficult for us to determine *ex ante* the reliability of measures constructed from the LVA technology. We therefore acknowledge that our results are going to be influenced by the reliability of the nonverbal measures. To the extent that these measures have considerable measurement error, it would bias against finding the relationships we hypothesize. In addition, the vocal parameters captured by

[9] We do not consider two other fundamental variables, i.e., global stress and thinking level, because it is unclear whether a stressed individual is stressed for good news reasons or bad news reasons. Similarly, it is unclear whether someone who is thinking extensively means good news or bad news. We also do not consider "conclusion" level variables as they are meant to enable markings of deception. Since we are not interrogating subjects and are not interested in deception per se, we focus our attention on fundamental variables that are reasonably theorized to have connotations of good and bad news.

[10] In the limit, a high emotion level is likely when the context is either deceptive or traumatic in nature. To the extent that such situations dominate in the determination of the *PAFF*, it will bias against finding the predicted relation.

the LVA technology measure cues that are often subtle and sometimes inaudible to the human ears, and hence analysts and investors listening in on the conference call may not detect and/or process these cues without the aid of computer software. Hence, we may not observe a relation between these measures and contemporaneous stock returns or analyst forecast revisions.

III. Sample Selection, Variable Measurement, and Descriptive Statistics

We derive our sample of audio files from all conference calls held between January 1 and December 31, 2007 available on the Thomson StreetEvents database. We face two main challenges with processing the audio files available on this database. First, Thomson Financial does not retain audio files indefinitely. Rather, they archive the audio files for a time period ranging from 90 days to one year following the conference call date, after which they are no longer available to database subscribers.[11] Second, StreetEvents provides access to audio files as playback only, thus the audio files cannot be downloaded directly. Together, they impose a time constraint on our analysis of the audio files, as we must manually play and analyze the audio files while such files are available. To accommodate this, we constructed our sample in two phases.

In the first phase, for the period between January 1 and March 31, 2007 we identify 2,650 conference calls of fiscal year 2006 4th quarter earnings where company identifiers are available on the CRSP, Compustat and I/B/E/S databases. We then remove 1,569 observations where StreetEvents does not index the audio file. Audio indexing is required for utilizing the LVA software, as discussed further below. We then remove 466 observations for which missing data on CRSP, Compustat or I/B/E/S prevents the construction of variables needed for the empirical tests we will subsequently employ. Thus, the final initial sample in phase I consists of 615 firm conference call observations that we analyze using the LVA software.

To construct our measures of managerial affect during conference calls, we playback the entire conference call audio files through LVA. The software requires a calibration period over which "normal" voice characteristics of the speaker are measured. Subsequent to calibration, LVA analyzes audio output

[11] Discussions with Thomson StreetEvents suggest that the archiving period is primarily determined by the firms.

at constant intervals relative to the calibration benchmark and produces various measures, including our variables of interest, cognition level and emotion level, which serve as the basis for negative and positive affect. LVA measurement continues until the researcher manually ends the test.

The earnings conference call audio files provided by StreetEvents are uniquely suited for LVA analysis for three reasons. First, firm executives commonly begin the conference call with mundane introductions of the conference call participants and Safe Harbor statements. These “boilerplate” opening statements are ideal for calibrating the voice of each executive because they require little cognitive investment. Second, StreetEvents has a proprietary technology called “indexed audio” that maps audio files onto the conference call transcripts. With indexed audio, a researcher can point and click to specific locations of the entire conference call where a given executive speaks. Since voice analysis is speaker dependent, the use of audio indexing allows us to seamlessly isolate the vocal content for a given executive throughout a conference call dialog without the confounding effects of other speakers. Lastly, the LVA software is geared specifically towards settings where subjects encounter intense interrogation and hence, we anticipate that the software is most powerful in detecting emotional states during analyst questioning.

For each conference call, we separately measure positive and negative affect for the CEO and CFO because each individual speaker has a different vocal pattern that requires separate calibration. We calibrate each executive based on their introductory remarks in the call presentation. If an executive does not provide introductory remarks in the conference call we calibrate his vocal pattern using the opening moments of his speech during the conference call. The calibration is done internally in the software, and typically only takes around ten seconds to complete. We aggregate the affect measures obtained for both executives present in a call to obtain firm level *NAFF* and *PAFF* measures.[12] LVA measures each

[12] We do not analyze CEO and CFO affective states separately because we expect both executives to have similar information sets and similar appraisals of such information, yielding similar affective states. The pearson correlation coefficients between CEO and CFO *PAFF* and *NAFF* measures separately are positive and statistically significant (ρ= 0.28 and 0.59; p = 0.00).

parameter approximately 35 times per minute. This implies for a 10 minute CEO speech, LVA will generate 350 parameter readings.

To generate conference call level measures of *NAFF* and *PAFF*, we measure how many individual cognition level and emotion level readings from each executive were above the "critical" level as defined by the developers of LVA. We count the number of "critical" instances and scale it by the total number of individual readings.[13] With respect to the cognition level, readings above 120% are indicative of severe cognitive dissonance by the subject. Hence, we use the proportion of readings that have cognition levels above 120% to construct the *NAFF* measure. For *PAFF*, we measure the proportion of readings with emotion levels greater than the critical 110% level. Figure 1 reproduces a screen shot from LVA for one CEO in our sample and depicts a graph that contains the various values of specific parameters LVA measures. The actual values of cognition level and emotion level graphically depicted are exported to a data file which is subsequently processed to obtain the *NAFF* and *PAFF* values.

Panel A of Table 1 presents the descriptive statistics for the emotion measures for the conference calls in the initial sample. The mean (median) for *PAFF* is 0.1028 (0.1039) indicating that on average, managers exhibit positive affect 10% of the time during a conference call. In contrast, managers exhibit negative affect about 17% of the time (mean *NAFF* = 0.1663).

A disadvantage of a small sample from a single calendar quarter is the difficulty in drawing clear and generalizable inferences due to lack of statistical power. At the same time, enormous costs of manual playback and analysis of individual executives throughout an entire conference call presents a significant challenge, particularly because of the finite availability of the audio files. As a compromise, we expanded our sample by analyzing conference call audio files of a shorter duration for the three subsequent calendar quarters of 2007.

[13] Ex-Sense Pro R only graphically produces the individual parameters that are needed for our empirical measures. We thank Nemesysco for accommodating our request to build a module into the software that allows us to extract the numerical values of the two vocal attributes we study that are otherwise only available in graphical format.

Conceptually, the software was developed to capture the emotional states during interrogation settings where the subject is asked questions to determine whether the subject exhibits a cognitive or emotional state different from their "normal" state. Furthermore, affective state is most powerfully elicited when external stimuli is the strongest. Thus, we believe that focusing on the Q&A portion of the call would give us the best chance of success in capturing affective states.

To determine the most cost effective duration, we partitioned the presentation and the Q&A portion of the initial sample of conference calls pertaining to the CEO into quartiles. We focus on the CEO rather than the CFO because the CEO arguably has the most knowledge about, and is most responsible for, a firm's performance. Moreover, CEOs tend to speak a lot more during the conference call relative to CFOs. In our initial sample, we find (results not tabled) that the average number of words spoken by the CEO (3,186) is statistically and economically greater than the average words spoken by the CFO (1,928).

We analyze the distribution of the two measures *PAFF* and *NAFF* for the CEO as the call progressed so as to identify the particular portion of the conference call that would be both economically and statistically meaningful. Results presented in Panels B and C suggest that both emotion measures display a gradually increasing trend throughout the conference call, consistent with what one would expect as a speaker approaches and begins to answer questions from an analyst audience in real time. In addition, we find a pronounced increase *NAFF* during the first quartile of the Q&A portion of the call (average CEO *NAFF* increases by 6.10%, from 16.94 to 17.97).

Based on conceptual underpinnings and preceding analysis, we decided to augment our initial sample by collecting the first 5 minutes of the CEO responses from question and answer portion of the conference call. By collecting a shorter duration we may be missing out on important affect variation, because as shown in Table 1 Panel B and C, *PAFF* and *NAFF* levels are still relatively high with considerable variance at *all* points during the conference call.[14] However, a shorter duration allows us to

[14] The presence of some emotion during the presentation portion of the conference is not surprising. Managers rationally anticipate some of the questions analysts will likely ask when preparing the presentation portion of the

analyze many more firm quarters over a longer time period, which increases external and statistical conclusion validity. To examine the empirical validity of using a shorter duration, for the initial sample, we estimated the correlation between the overall *PAFF* (*NAFF*) for the entire conference call with that of the *PAFF* (*NAFF*) computed for the first 5 minutes of the CEO responses during the Q&A section and find that the correlation is quite high (ρ for *PAFF* = 0.53; *NAFF*= 0.79). This gives us some confidence that the LVA measures computed for a shorter duration would capture statistically meaningful variation in the affective states.

Our second phase of data collection yields 1,032 firm quarter conference calls hosted from April 1, 2007 until December 31, 2007. Together, the two phases of data collection yield a final sample 1,647 observations representing 691 unique firms. Our final sample has far fewer observations in the 2nd calendar quarter of 2007 because by the time we made our decision to collect more data Thomson StreetEvents had purged the voice files for several of our sample firms.

We obtain stock return data from the CRSP database and www.yahoo.com as necessary. We obtain financial data from the Compustat database to the extent it is available. For financial data relating to the most recent periods, we hand-collect it from the Edgar database at www.sec.gov. We obtain analyst expectations of earnings and earnings forecast revision data from I/B/E/S.

Descriptive statistics for the combined sample are presented in Panel A of Table 2. The mean (median) for *PAFF* is 0.1086 (0.1064) whereas the mean (median) for *NAFF* is 0.1758 (0.1721). These descriptives are comparable to that obtained for the initial sample (see Panel A of Table 1) suggesting that the augmented sample is quite representative. The sample firms have an average (median) quarterly return on assets (*ROA*) of 0.41% (1.03%) and assets of \$7.6 (\$1.2) billion. The mean (median) firm has revenues of \$941 million (\$213 million) and market value of equity of \$5.7 billion (\$1.3 billion) (results not tabled). Thus, our sample has predominantly large firms. In Panel B we provide the industry composition

conference call, thereby endogenizing some the emotional effects that would otherwise be present during the question and answer period of the conference call.

for our sample firms. While we do not observe significant industry clustering, the sample contains a relatively greater number of firms from the computer, financial, and services industries.

The pearson correlation matrix of all the financial variables and the two affect measures are presented in Panel C of Table 2. Several observations are worth noting. First, *NAFF* is negatively related to size (*LNMVE*) (ρ = -0.15, p = 0.00), negatively related to firm profitability (ρ (*ROA,NAFF*) = -0.09, p = 0.00), and positively related with *VOL* (ρ = 0.11, p = 0.00). These correlations serve as construct validity checks for the affect variables computed by the LVA software. Recall that *NAFF* is based on measures of cognitive dissonance. For managers who believe they are competent and in control of their firms, poor accounting performance will cause cognitive dissonance because it undermines the manager's belief about competency. Additionally, if small firms and firms with high volatility capture settings that are more uncertain, it is likely that managers who believe they are in control of the firm will experience cognitive dissonance. We do not find statistically significant correlations between *PAFF* and the aforementioned variables, however.

Second, we do not observe a strong systematic relation between the two affect measures (ρ = 0.04, p = 0.11). This is not surprising because managers discuss many issues during a conference call, each of which may induce a positive or negative affect on the manager.[15] Further, research suggests that positive and negative affect need not be negatively correlated (Diener and Emmons, 1985, Cacioppo and Bernston, 1994). The lack of relation also suggests that neither affect measure subsumes the other in a univariate sense.

Third, we find some evidence that the affect variables convey information to the capital markets. The contemporaneous market reaction to *NAFF (PAFF)* is weakly (significantly) negative (positive) and of similar absolute magnitude (ρ = -0.04, p = 0.13; ρ = 0.05, p = 0.05). Further, for *NAFF* we find a

[15] Some firms explicitly attempt to provide a balanced view of the firm such that a portion of their conference call presentation is dedicated to positive aspects of the firm and another portion to negative aspects. Managers may provide a balanced perspective in the Q&A section as well. For example, Cisco Systems noted the following in its Q1 2004 earnings conference call: "Reminding those who have limited exposure to our prior conference calls, we try to give equal balance to both what went well and our concerns." This implies a positive correlation between *NAFF* and *PAFF*, as each unit of *NAFF* is balanced with a unit of *PAFF*.)

negative association with earnings news two quarters in the future, UE_{t+2}, (ρ = -0.09, p = 0.00). Since earnings news is based on analyst expectations of future earnings, the association of *NAFF* with future earnings news implies that analysts have not taken into account the implications of negative affect into their earnings forecasts contemporaneously. The negative correlation between *NAFF* and stock returns over the subsequent 180 days (ρ = -0.05, p = 0.05) suggests that investors appear to incorporate the implications of *NAFF* for future earnings news with some delay.[16] Collectively, these results provide some initial evidence to suggest there is information in affect conveyed via voice, and that the implications of negative affect take longer to get incorporated into price. Naturally, to draw more definitive conclusions about the role of affect as a source of information and how market participants incorporate such information, we must rule out confounding factors, as we do in our multivariate tests that follow.

IV. Results

A. Do Market Participants Respond to Managerial Affect?

We begin by assessing whether investors respond to managerial affect by examining the contemporaneous stock market reaction to vocal cues. We estimate daily abnormal returns using the returns on the size-BE/ME portfolio in which the firm resides (Fama and French, 1993) as the benchmark return, and then regress the two-day cumulative abnormal returns measured around the conference call date (*CAR(0,1)*) on the vocal cue measures, *NAFF* and *PAFF*. We control for quantitative accounting news contained in the earnings conference call by including the magnitude of unexpected earnings (*UE*), with expectations based on the last summary consensus median analyst forecast prior to the earnings conference call. We expect a positive coefficient on *UE*.

We next consider whether the vocal cue–based measures capture information incremental to that contained in the linguistic tone documented in prior research. We use the positive word and negative

[16] Johnson (2004) argues that firms with high idiosyncratic uncertainty have increased option values that expire over time and yield negative future stock returns. Since *NAFF* is positively correlated with idiosyncratic return volatility (*VOL*), an alternative explanation for the negative relation between *NAFF* and future stock returns is that *NAFF* simply captures firm specific idiosyncratic uncertainty. In our multivariate analysis, we control for idiosyncratic return volatility.

word dictionaries of Loughran and McDonald (2009) to compute the unexpected percentage of positive words (*POSWORDS*) and negative words (*NEGWORDS*) in the entire conference call dialog.[17] We expect a positive (negative) coefficient on *POSWORDS* (*NEGWORDS*).

We control for size, growth and risk that has been shown to be related to market returns (Collins and Kothari, 1989; Easton and Zmijewski, 1989)). We use the natural logarithm of market value of equity at the end of the current quarter (*LNMVE*), book to market ratio (*BM*) calculated as the book value of shareholders equity at the end of the current quarter scaled by the market value of equity, and return volatility (*VOL*) measured as the standard deviation of daily stock returns over 125 trading days prior to the earnings announcement date as the empirical proxies for size, growth, and risk respectively. Finally, we control for return momentum (*MOM*) measured as the cumulative daily abnormal return over the 125 day trading window [-127,-2] prior to the earnings announcement. We estimate the following specification:

$$CAR(0,1) = \lambda_0 + \lambda_1\, PAFF + \lambda_2\, NAFF + \lambda_3\, UE_t + \lambda_4\, LNMVE + \lambda_5\, MOM + \lambda_6\, BM + \lambda_7\, VOL + \lambda_8\, POSWORDS + \lambda_9\, NEGWORDS + \varphi \qquad (1)$$

We estimate equation (1) using pooled ordinary lease squares regression and use robust stadard errors. Column (1) of Table 3 presents the results of estimating equation (1). As expected, the coefficient on unexpected earnings (UE_t) is positive and statistically significant suggesting that the market responds significantly to the extent of news contained in the earnings announcement. Consistent with Davis et al.'s (2007) analysis of earnings press releases, we find a statistically significant positive (negative) relation between the *POSWORDS* (*NEGWORDS*) and contemporaneous returns.

More important, with respect to our variables of interest, we observe a significantly positive relation between positive affect (*PAFF*) and returns (coefficient = 0.1647; p-value <0.05). However, the coefficient on negative affect (*NAFF*), although negative, does not achieve statistical significance at conventional levels. This indicates that investors on average perceive positive information from positive affect but no information in negative affect. There are two possible explanations for the weak result for

[17] The positive word and negative word dictionaries are available at http://www.nd.edu/~mcdonald/Word_Lists.html.

NAFF. Investors may be optimistic, on average, and fail to incorporate the negative affective state in comparison to the positive affective state. An alternative explanation is that analysts are not scrutinizing enough in their exchange with management during earnings conference calls that might invoke the negative affective state. To test these competing explanations we identify situations where the analysts are most likely to scrutinize and interrogate managers during conference calls.

Recent survey evidence by Graham, Harvey and Rajgopal (2005, p. 42) points to such a situation: "CFOs dislike the prospect of coming up short on their numbers, particularly if they are guided numbers, in part because the firm has to deal with extensive interrogations from analysts about the reasons for the forecast error, which limits their opportunity to talk about long-run strategic issues". Therefore, we posit that managers of firms who miss analysts' earnings benchmarks are most likely to be extensively interrogated, in turn invoking affective states.[18]

To test this hypothesis, we define high scrutiny affect, $PAFF^{HS}$ ($NAFF^{HS}$), as *PAFF (NAFF)* when UE_t is less than zero, and zero otherwise. We define low scrutiny affect, $PAFF^{LS}$ ($NAFF^{LS}$) as *PAFF (NAFF)* when UE_t is greater than or equal to zero, and zero otherwise. These definitions allow the coefficient on *PAFF* and *NAFF* to vary depending on whether the firm is in a high or low scrutiny setting, where scrutiny is based on sign of the deviation of the firms reported earnings from analyst expectations. We then estimate the following specification:

$$\begin{aligned} CAR(0,1) = \lambda_0 &+ \lambda_1\, PAFF^{HS} + \lambda_2\, NAFF^{HS} + \lambda_3\, PAFF^{LS} + \lambda_4\, NAFF^{LS} + \lambda_5\, UE_t \\ &+ \lambda_6\, LNMVE + \lambda_7\, MOM + \lambda_8\, BM + \lambda_9\, VOL + \lambda_{10}\, POSWORDS \\ &+ \lambda_{11}\, NEGWORDS + \varphi \qquad (2) \end{aligned}$$

Regression results from estimating equation (2) are presented in column (2) of Table 3. Allowing the effects of *PAFF* and *NAFF* to vary by the extent of scrutiny improves the model fit substantially, as evidenced by the increase in adjusted R^2 from 7.64% to 10.65%. Our evidence is consistent with

[18] In unreported results, we test whether analysts are more scrutinizing in conference calls when firms miss analyst expectations. We collect all transcripts from Thomson StreetEvents during the period 2002-2004 and examine the words spoken between management and each individual analyst during the question and answer session. We find that the firms that miss analyst forecasted earnings have less positive (more negative) dialogs during the Q&A. Consistent with increased scrutiny, analysts with relatively favorable stock recommendations, who otherwise exchange more favorable words with management, are more negative when the firm misses earnings targets. In fact, the extent of scrutiny by favorable and unfavorable analysts is no longer statistically different.

analysts being more scrutinizing when earnings expectations are not met that in turn evokes emotions, rather than a failure on the part of investors to incorporate negative affective state exhibited by CEOs.[19] In particular, we find that the coefficient on $NAFF^{HS}$ is negative and statistically significant (coefficient -0.1522; p-value <0.01). The coefficient on $PAFF^{HS}$ is positive and statistically significant (coefficient 0.1507; p-value <0.05), and is of similar magnitude with that on $NAFF^{HS}$. While there are no observed differences in the market perceptions of positive affective state across scrutiny conditions (an F-Test for the equality of the coefficients on $PAFF^{HS}$ and $PAFF^{LS}$ cannot be rejected), the market does not react to negative affective state for firms in low scrutiny conditions ($NAFF^{LS}$ = 0.0432, p-value > 0.10) and an F-Test for the equality of the coefficients on $NAFF^{HS}$ and $NAFF^{LS}$ is rejected (p-value < 0.01). These results imply that the market reaction to negative affect is statistically greater, and only exists, when firms are in high scrutiny conditions.[20]

To better understand the nature of the affect based news investors respond to, we examine whether and how analysts incorporate the signals in the vocal cue–based measures when revising their expectations about the firm's financial future. If the news in positive (negative) affect is informative to analysts, we would expect to see upward (downward) revisions in earnings forecasts, stock recommendations, or both. Given the results in Table 3 that investors react to both positive and negative affect in high scrutiny conditions, we will pay particular attention to that setting in our remaining empirical analysis.

To examine analyst reactions, we use analyst forecast revision (*FREV*) and changes in analyst recommendations (*RECREV*) as the dependent variables instead of *CAR(0,1)* in equation (2). We include the contemporaneous market reaction *CAR(0,1)* as an additional explanatory variable to control for news

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[19] We find that the coefficient on unexpected earnings is no longer statistically significant after allowing the effects of emotion to vary in high and low scrutiny conditions. This should not be interpreted as the information in emotion subsuming the effects of quantitative earnings news. The relation between contemporaneous stock returns and unexpected earnings has been shown to be nonlinear (Freeman and Tse 1992; Kinney et al. 2002). Accommodating this nonlinearity in the earnings-returns relation reveals that stock returns are increasing in unexpected earnings in a statistically significant way and the inferences on our emotion based variables remain unchanged.

[20] A competing explanation for this finding is that investors are more attuned to the conversation during conference calls when earnings expectations are missed, rather than extensive scrutiny by managers. However, our subsequent finding that investors fail to fully incorporate the implications of negative affect when earnings expectations are not met is inconsistent with this explanation (see Table 6).

in the earnings release that is not quantifiable by our other control variables. We expect a positive coefficient on *CAR(0,1)* consistent with our other news proxies. Our expectations for the other explanatory variables are identical to equation (2).

We measure analyst forecast revisions (*FREV*) as the one quarter ahead forecast revision representing the difference between the median one quarter ahead forecast issued after and before the current period earnings announcement, scaled by stock price two days preceding the conference call.[21] The median forecast before (after) the current period earnings announcement is determined using the last (first) forecast of all individual analysts issuing forecasts during the 90 day period before (after) the current quarter earnings announcement date. We measure recommendation revision (*RECREV*) as the difference between the average consensus recommendation immediately after and before the earnings announcement. Consensus recommendations are measured as the average of recommendations across all analysts. In determining the average, strong buy recommendations are coded as 5, buy recommendation as 4, hold as 3, sell as 2 and strong sell as 1.

The results are reported in Table 4. For the forecast revision regression, the coefficients on the managerial affect measures in the high scrutiny condition, $PAFF^{HS}$ and $NAFF^{HS}$, are statistically insignificant. This implies that the analysts do not take into account the information contained in the affect measures when revising their earnings expectations for the upcoming quarter. Consistent with prior work, we find that analysts significantly revise their next period forecast based on the nature of unexpected earnings (coefficient on UE_t = 0.1273; p value < 0.01) and the market's interpretation of earnings (coefficient on *CAR(0,1)* = 0.0111; p value < 0.01).[22] We find no association between linguistic tone and forecast revision activity.

One plausible explanation for our finding the analysts do not incorporate the information contained in the affective state is that the news does not map into a firms immediate next quarter earnings.

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[21] Observations (128 firms) with no individual analyst forecast revisions during the period are set to zero values. We re-estimated the regression after eliminating the 128 firms and our inferences remain unchanged.
[22] Inclusion of the contemporaneous market reaction as a proxy for other earnings information we cannot explicitly control may result in controlling away the potential effects of *NAFF* and *PAFF*. Re-estimating Table 4 Column 1 by excluding *CAR(0,1)* from the estimation yields inferences that are similar to those presented.

Rather, it contains soft information that analysts may incorporate into their longer term projections of the firm performance in metrics like stock recommendations (see Bradshaw 2004). To consider this explanation, we investigate changes in analyst recommendations, arguably a broader measure, and admittedly a coarser measure, of changes in analyst expectations. We include the level of analyst recommendations immediately prior to the earnings announcement (*LAGREC*) as an additional independent variable to control for potential nonlinearity in the changes variables given the truncated distribution of the level of recommendations. For example, an increase (decrease) in recommendation cannot occur for a recommendation that is already a strong buy (sell). Including this variable also controls for potential mean reversion in recommendations. We predict a negative coefficient for *LAGREC*.

Results presented in column (2) of Table 4 indicate that in the high scrutiny condition, analysts on average incorporate the positive affective state when making recommendation changes (coefficient of $PAFF^{HS} = 0.4200$; p value < 0.05). We do not find significant results for negative affective state under either scrutiny conditions, which is potentially consistent with two explanations. Either analysts do not understand negative affect or analysts do understand negative affect and act on incentives to avoid incorporating such negative information into their stock recommendations (O'Brien et al. (2005)). Subsequent analysis provides support more for the latter explanation than the former.

We do not observe a relation between linguistic measures and recommendation changes. Combining this result with the finding in Engelberg (2008) that linguistic tone in earnings press releases predict future stock returns, one can conclude that part of the reason why linguistic tone predicts future returns is that analysts do not alert investors regarding the future performance implications of linguistic tone.

To summarize, in high scrutiny settings where the ability to detect emotional states is most pronounced, the contemporaneous reactions by investors provides support for the hypothesis that investors perceive news in vocal cue measures. Analysts do not appear to incorporate the information contained in vocal cue measures in determining near term earnings forecasts but do so asymmetrically in their stock recommendations.

B. Does Managerial Affect Predict Future Firm Performance?

In this section we formally investigate whether vocal cues provide insights into managerial affective states that in turn inform about future firm performance. In particular, we test the hypothesis that the investors' response to vocal cues is consistent with these measures providing novel information about future earnings realizations. We focus on unexpected future earnings as a proxy for the potential cash flow news inherent in the capital market response. Specifically, we use future analyst forecast error scaled by stock price two days before the period t conference call (*UE*) as our proxy for future firm performance. Analyst forecast error is computed as the difference between the actual earnings per share minus the summary consensus median earnings forecast immediately prior to the earnings announcement.

We estimate the following empirical specification:

$$\begin{aligned} UE_{t+1,t+2} = {} & \beta_0 + \beta_1\, PAFF^{HS} + \beta_2\, NAFF^{HS} + \beta_3\, PAFF^{LS} + \beta_4\, NAFF^{LS} + \beta_5\, UE_t \\ & + \beta_6\, FREV + \beta_7\, FDISP + \beta_8\, LNMVE + \beta_9\, MOM + \beta_{10}\, BM + \beta_{11}\, VOL \\ & + \beta_{12}\, POSWORDS + \beta_{13}\, NEGWORDS + \varepsilon \end{aligned} \tag{3}$$

We consider unexpected earnings up to two quarters ahead because we are unable to obtain future earnings for all the firms beyond two quarters.[23] If the vocal cue measures contain useful information about future performance consistent with the market perceptions, we would expect a positive (negative) coefficient on $PAFF^{HS}$ and $NAFF^{HS}$. In equation (3) we also includes several other control variables that have been shown to affect future unexpected earnings such as analyst forecast revisions, forecast dispersion, firm size, return momentum, book-to-market ratio and return volatility.

We measure forecast dispersion (*FDISP*) as the standard deviation of analysts' earnings per share forecasts derived from the distribution of I/B/E/S consensus earnings per share forecasts immediately prior to the earnings announcement.[24] All other variables have been previously defined.

[23] Our results for three quarters ahead unexpected earnings for a reduced sample are similar.
[24] Inferences are unchanged when we scale the dispersion of analyst forecasts with either the absolute value of actual earnings per share or the standard deviation of earnings per share.

Table 5 presents the regression results from estimating equation (3). We present results from one period ahead and two-period ahead unexpected earnings in column (1) and column (2) respectively. In column (3) we reports results using the aggregate unexpected earnings for the two periods as the dependent variable. The coefficient on unexpected earnings is positive and statistically significant across all three columns, indicating the persistence in unexpected earnings. Results in column (1) indicate that although higher levels of excitement (*PAFF*) and cognitive dissonance (*NAFF*) exhibited by executives under both scrutiny conditions are positively and negatively associated with future unexpected earnings, the statistical significance do not reach conventional levels. This may be because the information contained in the vocal cues may extend beyond one period. Consistent with this conjecture, we find that the vocal cue measures in the high scrutiny condition predict two period ahead unexpected earnings (coefficient on $PAFF^{HS}$ is 0.0690, p-value < 0.05; coefficient on $NAFF^{HS}$ is -0.0307, p-value < 0.05). Our findings are similar when we combine one period and two period ahead unexpected earnings (column (3)).

These findings obtain after controlling for information contained in the reported earnings number and linguistic content of the conference calls. Not surprisingly, unexpected earnings are a potent predictor of future unexpected earnings. We find no statistical association between words spoken during the conference call and future unexpected earnings, however. Overall, our findings suggest that affective states possess incremental information to linguistic tone in predicting future unexpected earnings, particularly when managers miss current period analysts' earnings estimates.

C. Does Managerial Affect Predict Future Stock Returns?

Based on the evidence thus far, we can conclude that nonverbal vocal cues have significant information content for future firm performance, particularly when analysts engage in scrutinizing managers. However, the evidence presented with respect to analyst forecast revision and recommendation changes suggests that analysts may not fully incorporate the information contained in these vocal cues. Past accounting literature has documented price drift with respect to quantitative earnings information (Bernard and Thomas, 1989; Doyle et al. 2006) and with respect to optimistic and pessimistic language

(Demers and Vega, 2007; Engelberg, 2008). To the extent that the market fails to fully appreciate the implications of the nonverbal signals we investigate here, we expect a systematic relation between the vocal cues and future stock returns. Therefore, in this section, we test whether this information subsequently gets incorporated into stock price.

Alternatively stated, we examine whether the affect measures can help predict future abnormal returns. Because stock returns reflect revisions in future expectation of cash flows and earnings, we expect that the information contained in the affect measures, although not fully incorporated in contemporaneous market returns, will likely be incorporated in future stock returns when the implications of these measures for future fundamentals subsequently realize.

We test this prediction by using the cumulative abnormal returns over the 180 trading days following two days after the earnings conference call *(CAR(2,180))*. We restrict our analysis to 180 days because we hand-collect returns data from www.yahoo.com and we stopped data collection on September 2008. Recall from Table 2 where we report correlation statistics that we observed a negative statistical association between negative affect (*NAFF*) and future abnormal returns (*CAR(2,180)*). In contrast, there was no statistically significant correlation between *PAFF* and future abnormal returns. The univariate results, however, do not account for other factors known to predict long run returns. Therefore, we estimate the following multivariate model that controls for risk and other factors shown to determine future stock returns:

$$\begin{aligned} CAR(2,180) = {} & \omega_0 + \omega_1\, PAFF^{HS} + \omega_2\, NAFF^{HS} + \omega_3\, PAFF^{LS} + \omega_4\, NAFF^{LS} + \omega_5\, UE \\ & + \omega_6\, LNMVE + \omega_7\, MOM + \omega_8\, VOL + \omega_9\, BM \\ & + \omega_{10}\, POSWORDS + \omega_{11}\, NEGWORDS + \xi \end{aligned} \tag{4}$$

The independent variables in model (4) are identical to model (2). Results of estimating equation (4) are presented in Table 6. The coefficient on UE_t is positive but not statistically significant (coefficient = 2.2959). This statistical insignificance is not surprising given that our sample is comprised of large firms and prior research shows that post–earnings announcement drift is much less pronounced in large firms (Bernard and Thomas, 1989). We find no statistical association between linguistic tone and future abnormal returns, consistent with Loughran and McDonald (2009) who find no predictive ability for linguistic tone and one year ahead returns.[25]

Pertinent to this study, we find that the coefficient on $NAFF^{HS}$ is negative and statistically significant at the 5% level (coefficient = -0.6463). This evidence is consistent with market participants under reacting to the information in negative affect exhibited by CEOs when analysts engage in extensive scrutiny of firm managers. We do not find a statistically significant association between positive affect in the high scrutiny condition and future returns (coefficient on $PAFF^{HS}$ = 0.5280). For the low scrutiny condition, neither *NAFF* nor *PAFF* are statistically significant.

It is difficult to ascertain why market participants fail to fully incorporate negative affect. However, one plausible explanation is consistent with our findings relating to asymmetric analyst recommendation changes following the conference call. Recall that in Table 4 we found evidence that analysts incorporate positive affect but not negative affect into their recommendations. If part of the contemporaneous market price response is a reaction to analyst recommendation changes into price, the lack of downgrading for negative affect would imply a less than complete market reaction to negative affect. Regardless, we caution the reader that this does not establish that we have a profitable trading strategy for two reasons. First, the time period we consider is not long enough for us to analyze calendar time returns that would help us make definitive conclusions regarding abnormal returns. Second, any returns to a trading strategy may be simply compensation for information acquisition costs (Grossman and Stiglitz, 1980) associated with learning about vocal cues.

IV. Additional Analyses

Thus far, we have three main findings: 1) vocal cues that reflect managerial affective states when analysts are scrutinizing managers predict future unexpected earnings; 2) market participants, investors and analysts respond to information contained in the vocal cues, at least partially; and 3) negative managerial affect predicts future returns. In this section, we explore whether the predictability of future

[25] Other researchers (Engelberg 2008; Demers and Vega 2007) document associations between future returns and linguistic tone when using the General Inquirer's *Harvard Phychosociological Dictionary*. Using that dictionary we also find negative (positive) tone is negatively (positively) associated with future stock returns.

returns stem from firm-specific news releases subsequent to the conference call and from the lack of analyst activity.

The predictive ability of managerial affect for future returns may stem from information contained in future realizations of fundamentals such as earnings or from other soft information that contain value relevant news. Because we capture vocal cues that are not content-specific, i.e., we do not attribute the positive and negative affect that arise during conference calls to specific issues that are discussed during the call, focusing on future earnings realizations would be limiting the implications of vocal cues for future firm fundamentals. It is plausible that the information in vocal cues may capture subsequent value relevant news events broader than earnings releases alone. To test this prediction, we use Lexis Nexis to obtain all press releases issued by firms (wire service stories from the Company's headquarters) in our initial sample during the 180 day window following two days after the conference call. We then code a press release as a bad news release if the abnormal stock returns surrounding the press release (window [0,1]) is negative. We take the proportion of bad news releases during the 180 day window as our measure of information following the conference call. We then estimate a two limit tobit model similar to equation (4) by replacing the dependent variable with the proportion of bad news to examine if the vocal cues predict future information outcomes.

Results presented in Table 7 suggests that under the both the high and low scrutiny conditions, managers who exhibit positive affective state have lower proportion of bad news releases subsequent to the conference call. Similarly, managers in high scrutiny settings who exhibit negative affective state have higher proportion of bad news releases, but this result is not statistically significant at conventional levels (one tailed p-value = 0.13). With respect to the linguistic tone measures, we find that negative words spoken during the conference call results in a statistically greater proportion of bad news releases, but we find no statistical association between positive words and news release proportions. Perhaps the analysis lacks statistical power either because the180 day window is insufficient to capture all the information events or because the sample size is still relatively small.

Next, we investigate the role of analysts in the observed drift in stock prices. The results thus far are consistent with either analysts understanding the negative implications of negative affect but not incorporating it into their public signals or with analysts not understanding the negative affect. To investigate this issue, we examine forecast revision activity of all analysts following the firm. If analysts understand the implications and are in turn remain silent, then we should observe a negative association between NAFF and the percentage of analysts who revise their annual forecasts after the earnings conference call. On the contrary, if analysts do not comprehend negative affect, we will observe no association between affect and revision activity. Panel A of Table 8 provides a two limit tobit estimation of the proportion of analysts covering each firm that revised an existing estimate of upcoming annual earnings subsequent to the conference call. The results reveal that of all affect measures, only negative affect in the high scrutiny condition has a significant coefficient, and the coefficient is negative. This implies that when analysts observe higher levels of negative affect they are less likely to revise their forecasts. Interestingly, we also observe a similar effect for negative linguistic tone. These findings are consistent with analysts' general reluctance to revise forecasts and recommendations downward on receiving bad news perhaps to obtain reciprocal benefits from managers (Westphal and Clement 2008).

Admittedly, analysts might remain silent in their public communication, but privately communicate to institutional clients their views (Irvine, Lipson and Puckett 2007). If this is the case, we should observe less drift in subsamples where institutional investment is high. In Panel B of Table 8, we partition the data and reestimate the relation between managerial affect and future stock returns across high and low levels of institutional holdings. We find that drift for negative affect is more pronounced for firms with low level of institutional holdings (coefficient of -0.89) relative to that for high level of institutional holdings (coefficient of -0.57). However, the difference is not statistically significant. As such, we cannot definitively conclude that analysts are "tipping" institutional clients privately.

Finally, we examine whether the managerial affective states merely captures managerial attributes rather than providing information that varies with context and firm-specific circumstances. Since we cannot be sure that the software calibration completely removes innate managerial attributes or that the emotions in voice measured by the software are completely voluntary rather than somewhat controllable, we explore the possibility that managers who have more overall and firm specific experience may have muted emotional expressions or at the extreme will be able to suppress their emotional state much better than younger and inexperienced managers. We test this hypothesis by including CEO age (*AGE*) and CEO tenure (*TENURE*) with the firm in models (2), (3) and (4). In untabulated results we find the following. First, the CEO of the average sample firm is about 54 years of age and has been with the firm for approximately 6 years, and both variables have significant variation across firms as the standard deviation for *AGE* (*TENURE*) is 7.2 (6.1). Second, the relation between managerial affective states and contemporaneous stock returns are unaffected by the inclusion of *AGE* and *TENURE*. This suggests that managerial attributes do not explain the information content of vocal cues. Our findings with respect to future unexpected earnings and future stock returns are similar to those reported previously (see columns (2) and (3)). We also interacted the *PAFF* and *NAFF* variables with *AGE* and *TENURE* to detect cross-sectional differences in the predictive ability of vocal cues for future performance. In unreported results we find that the interaction variables are statistically insignificant, indicating that age and tenure does not alter the extent of emotional leakage captured by the LVA software.

V. Conclusions

Our study is the first to provide evidence on the role of vocal cues as a source of information about firm's financial prospects. We posit that vocal cues from conversations with executives during earnings conference calls convey information about their affective states that, in turn, help predict future profitability and returns. We find that higher levels of positive (negative) affect, as operationalized via higher levels of excitement (cognitive dissonance) determined by proprietary LVA software, conveys good (bad) news about future firm performance. That is, investors respond to the information contained in the positive and negative effect as evidenced by the stock returns surrounding the conference call. The effects are most pronounced when the affective state is invoked when analysts scrutinize managers during conference calls, which occurs when firms miss analyst earnings estimates. More positive (negative) affect predicts two period ahead future earnings. This relation obtains even after controlling for quantitative information and managers' linguistic style or word usage during conference calls. Analysts respond asymmetrically to affective states, where we find a positive association between recommendation changes and positive affective states, but no association between recommendation changes and negative affective states. We also document that stock market participants under react to the information contained in vocal cues containing negative affect. We do not, however, claim that such under reaction represents an arbitrageable trading strategy. Such a conclusion cannot be reached without a detailed analysis of the impact of trading costs and information acquisition costs that require a longer time series of data.

An important implication of our paper is that information gleaned from nonverbal cues conveyed during communications between managers and shareholders may be quite useful in resource allocation and portfolio decisions. Thus our evidence adds to the body of research in social psychology that finds an incrementally important role for nonverbal cues in communication.

We view our evidence as provocative and offers encouragement to extend this line of inquiry in various ways. First, identifying which particular business transactions or events (such as restructurings, new customer agreements, restatements etc.) elicit positive or negative managerial affect can potentially lead to more powerful tests and further our understanding about how vocal cues can inform investors in a capital market setting. Second, our analysis could be utilized in other settings, such as how vocal cues from depositions and communications by the Federal Reserve chairman might assist in forecasting interest rates. Such an analysis would complement current work analyzing the predictive ability of the chairman's linguistic style (Piger, 2006; Bligh and Hess 2007). Finally, technological advances have increased the availability of video in addition to audio. Exploring facial expressions as yet another channel of nonverbal managerial communication in the context of financial markets would be a fruitful avenue for future research.

Figure 1 – Screen Shot of LVA analysis of audio files

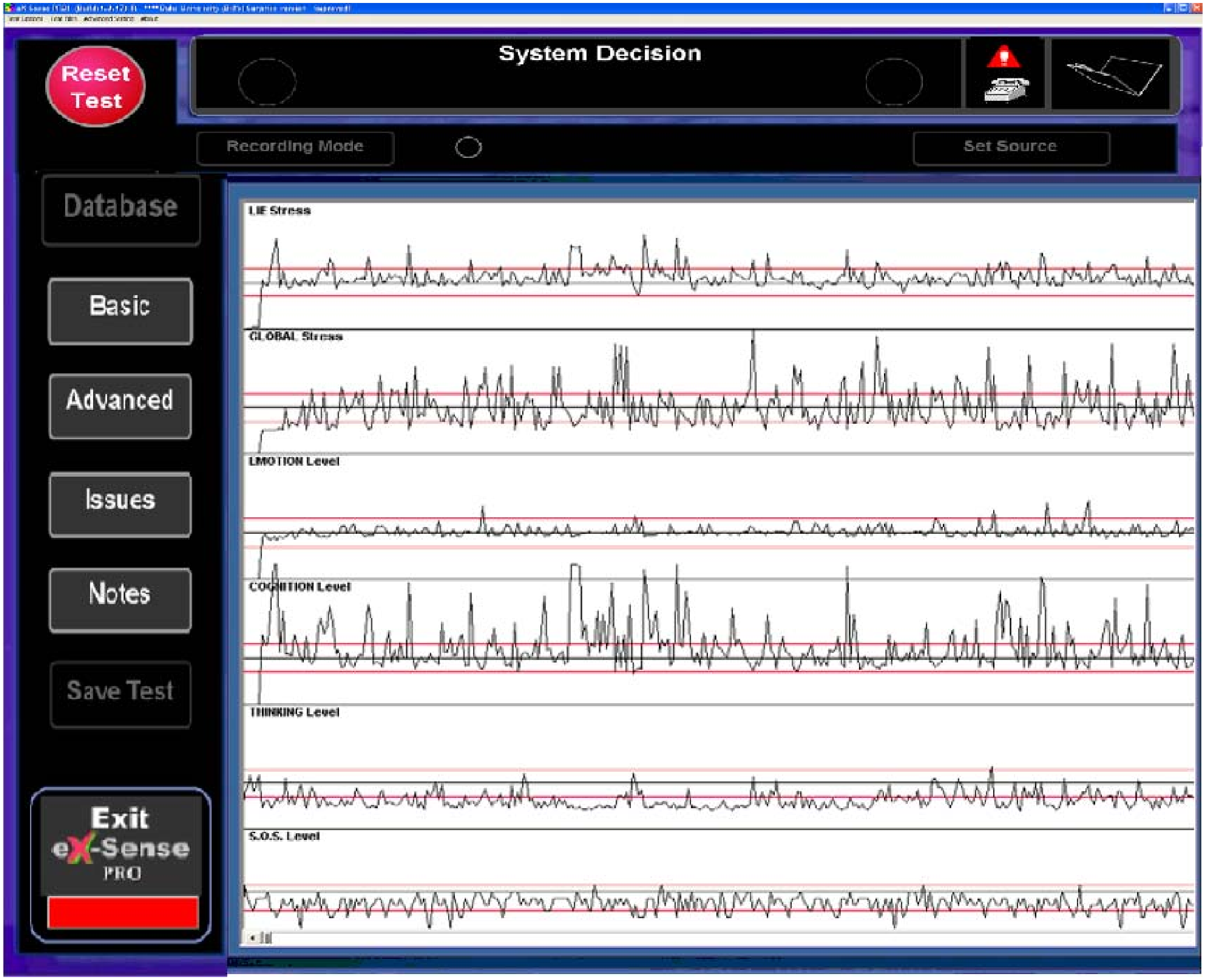

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Table 1
Initial Sample Descriptive Statistics on Affective State Variables

This table reports descriptive statistics on the affective state variables calculated for an initial sample 615 fiscal year 2006 4th quarter earnings conference calls occurring between January 1 and March 31, 2007. In Panel A, *PAFF* is positive affect measured as the percentage of CEO and CFO spoken audio during the entire conference call with Emotion Level scores above the critical value of 110 as measured by LVA; *NAFF* is negative affect measured as the percentage of CEO and CFO spoken audio during the entire conference call with Cognition Level scores above the critical value of 120 as measured by LVA. Panel B reports how *PAFF* evolves over the course of the conference call for CEOs. *PAFF* is calculated as in Panel A, except that it is only calculated for the CEO, and is measured at eight intervals: the four quintiles of the presentation portion of the conference call and the four quintiles of the question and answer session. Panel C reports how *NAFF* evolves over the course of the conference call for CEOs. *NAFF* is calculated as in Panel A, except that it is only calculated for the CEO, and is measured at eight intervals: the four quintiles of the presentation portion of the conference call and the four quintiles of the question and answer session.

Panel A: Descriptive statistics of *PAFF* and *NAFF*

Variable	N	Mean	Std Dev	Median	Min	Max
PAFF	615	0.1028	0.0174	0.1039	0.0347	0.1610
NAFF	615	0.1663	0.0644	0.1632	0.0256	0.3372

Panel B: Descriptive statistics – across sections of the conference call – CEO *PAFF*

Quartiles	Mean	Std Dev	Median	Mean change	Mean change %	p-value Mean change = 0
Presentation Section						
1	0.0948	0.0440	0.0934			
2	0.0978	0.0442	0.0956	0.0030	3.20%	
3	0.0972	0.0423	0.0967	-0.0006	0.60%	0.79
4	0.1061	0.0534	0.1004	0.0089	9.20%	0.00
Q&A Section						
1	0.1078	0.0402	0.1072	0.0017	1.60%	0.51
2	0.1103	0.0434	0.1083	0.0025	2.30%	0.24
3	0.1118	0.0441	0.1125	0.0015	1.40%	0.47
4	0.1132	0.0372	0.1117	0.0014	1.20%	0.51

Panel C: Descriptive statistics – across sections of the conference call – CEO *NAFF*

Quartiles	Mean	Std Dev	Median	Mean change	Mean change %	p-value Mean change = 0
Presentation Section						
1	0.1542	0.09667	0.1467			
2	0.1565	0.08869	0.1547	0.0022	1.50%	0.65
3	0.1601	0.09119	0.1538	0.0036	2.30%	0.45
4	0.1694	0.09088	0.1667	0.0092	5.80%	0.06
Q&A Section						
1	0.1797	0.08396	0.1721	0.0104	6.10%	0.03
2	0.1809	0.07788	0.1753	0.0012	0.70%	0.78
3	0.1879	0.07763	0.1851	0.0070	3.90%	0.09
4	0.1794	0.07125	0.1759	-0.0086	-4.60%	0.03

Tab1e 2
Descriptive Statistics and Sample Characteristics

This table reports descriptive statistics and sample characteristics for 1,647 quarterly earnings conference calls occurring between January 1 and December 31, 2007. *PAFF* is positive affect measured as the percentage of spoken audio by management during the conference call with Emotion Level scores above the critical value of 110 as measured by LVA; *NAFF* is negative affect measured as the percentage of spoken audio by management during the conference call with Cognition Level scores above the critical value of 120 as measured by LVA; *ROA* is return on assets measured as income before extraordinary items at the beginning of the quarter; *STDROA* is the standard deviation of *ROA* over the prior four fiscal quarters; *ASSETS* is total assets in millions at fiscal quarter end, *NEGWORDS* is the percentage of negative words, as defined by the Negative Words dictionary of Loughran and McDonald (2009), in the entire conference call dialog less the percentage of negative words in the entire conference call dialog of the firm's prior quarter earnings conference call; *POSWORDS* is the percentage of positive words, as defined by the Positive Words dictionary of Loughran and McDonald (2009), in the entire conference call dialog less the percentage of positive words in the entire conference call dialog of the firm's prior quarter earnings conference call; *FREV* is the analyst one quarter ahead forecast revision, measured as difference between the median forecast for quarter *t+1* earnings issued after and before the quarter *t* earnings announcement date, scaled by price two days before the earnings announcement. The median forecast before (after) the quarter *t* earnings announcement is measured as the last (first) forecast of all individual I/B/E/S analysts issuing forecasts during the 90 day period prior to (after) the quarter *t* announcement date; *RECREV* is the I/B/E/S summary consensus mean analyst recommendation revision, measured as the first I/B/E/S summary consensus mean after the conference call less the last I/B/E/S summary consensus mean before the conference call, where strong buy equals 5, buy equals 4, hold equals 3, sell equals 2 and strong sell equals 1; *FDISP* is the standard deviation of analyst per share earnings forecasts that comprise the summary consensus earnings estimate; *CAR(i,j)* is daily abnormal returns cumulated over day *i* through *j* relative to the earnings conference call date, where expected returns are derived from the size-BE/ME portfolio to which the firm belongs; UE_t is unexpected earnings at period *t* measured as the difference between actual I/B/E/S earnings per share and I/B/E/S analyst summary consensus median earnings per share scaled by price per share to days before the conference call; UE_{t+1} (UE_{t+2}) is unexpected earnings at period t+1 (t+2), whereas $UE_{t+1,t+2}$ is the aggregate unexpected earnings for t+1 and t+2. measured as the difference between actual I/B/E/S earnings per share and I/B/E/S analyst summary consensus median earnings per share scaled by price per share to days before the conference call; *LNMVE* is the natural logarithm of the market value of equity measured in millions at fiscal quarter end; *MOM* is momentum measured as *CAR(-127,-2)*; *BM* is the ratio of the book value of equity to the market value of equity at fiscal quarter end; *VOL* is the stock return volatility measured as the standard deviation of daily stock returns over the period (-127,-2) relative to the conference call date. Panel A reports descriptive statistics for the sample observations. Panel B reports industry concentrations for the sample observations. Panel C reports correlations between positive and negative emotional states and sample firm characteristics.

Panel A: Descriptive statistics

Variable	N	Mean	Std Dev	Median	Min	Max
PAFF	1,647	0.1086	0.0245	0.1064	0.0199	0.2391
NAFF	1,647	0.1758	0.0702	0.1721	0.0000	0.4570
ROA	1,647	0.0041	0.0455	0.0104	-0.2059	0.1156
STDROA	1,647	0.0148	0.0237	0.0063	0.0001	0.1523
ASSETS	1,647	7,658	21,441	1,227	29	143,369
NEGWORDS	1,647	0.0087	0.2243	0.0108	-1.0100	1.6000
POSWORDS	1,647	0.0092	0.2665	0.0105	-1.2000	0.9800
FREV	1,647	-0.0016	0.0056	-0.0002	-0.0344	0.0121
RECREV	1,647	0.0017	0.2006	0.0000	-2.0000	1.5000
FDISP	1,647	0.0344	0.0519	0.0200	0.0000	0.3600
CAR(0,1)	1,647	-0.0023	0.0787	-0.0019	-0.4983	0.3319
CAR(2,180)	1,647	-0.0612	0.4218	-0.0210	-3.6617	1.7641
UE_t	1,647	-0.0008	0.0129	0.0004	-0.0903	0.0310
UE_{t+1}	1,647	-0.0016	0.0177	0.0004	-0.1344	0.0409
UE_{t+2}	1,146	-0.0020	0.0210	0.0004	-0.1719	0.0383
$UE_{t+1,\, t+2}$	1,146	-0.0028	0.0312	0.0009	-0.3063	0.0792

LNMVE	1,647	7.2762	1.5544	7.1625	3.9519	11.4565
MOM	1,647	-0.0035	0.2404	0.0035	-0.7190	0.6579
BM	1,647	0.4404	0.2854	0.3942	-0.1132	1.4327
VOL	1,647	0.0212	0.0086	0.0198	0.0078	0.0514

Panel B: Industry Composition

Industry	**Sample Firms**		**All Compustat Firms**	
	N	**%**	**N**	**%**
Chemicals	30	1.82	411	1.82
Computers	236	14.33	2,908	12.85
Extractive	59	3.58	904	3.99
Financial	218	13.24	3,050	13.48
Food	23	1.40	401	1.77
Insurance/RealEstate	117	7.10	2,306	10.19
Manf:ElectricalEqpt	51	3.10	767	3.39
Manf:Instruments	110	6.68	1,062	4.69
Manf:Machinery	28	1.70	544	2.40
Manf:Metal	20	1.21	473	2.09
Manf:Misc.	8	0.49	214	0.95
Manf:Rubber/glass/etc	9	0.55	371	1.64
Manf:TransportEqpt	30	1.82	340	1.50
Mining/Construction	28	1.70	622	2.75
Pharmaceuticals	124	7.53	900	3.98
Retail:Misc.	93	5.65	933	4.12
Retail:Restaurant	19	1.15	286	1.26
Retail:Wholesale	28	1.70	781	3.45
Services	178	10.81	2,064	9.12
Textiles/Print/Publish	80	4.86	845	3.73
Transportation	102	6.19	1,388	6.13
Utilities	50	3.04	658	2.91
Not assigned	6	0.36	405	1.79
Total	1,647	100.00	22,633	100.00

Panel C: Pearson Correlations among emotion levels and firm characteristics (significance levels in parentheses)

	PAFF	***NAFF***
NAFF	0.04	
	(0.11)	
ROA	0.01	-0.09
	(0.80)	(0.00)
STDROA	0.01	0.04
	(0.63)	(0.15)
ASSETS	0.01	-0.12
	(0.82)	(0.00)
POSWORDS	-0.03	-0.01
	(0.20)	(0.60)
NEGWORDS	-0.01	0.03
	(0.70)	(0.21)
FREV	-0.00	-0.03
	(0.86)	(0.26)
RECREV	0.03	0.01
	(0.21)	(0.61)
FDISP	0.02	-0.00
	(0.49)	(0.91)
CAR(0,1)	0.05	-0.04
	(0.05)	(0.13)
CAR(2,180)	-0.00	-0.05
	(0.87)	(0.05)
UE_t	-0.00	-0.04
	(0.93)	(0.14)
UE_{t+1}	0.01	-0.04
	(0.66)	(0.12)
UE_{t+2}	0.02	-0.09
	(0.40)	(0.00)
$UE_{t+1,t+2}$	0.01	-0.09
	(0.68)	(0.00)
LNMVE	0.01	-0.15
	(0.56)	(0.00)
MOM	-0.01	-0.05
	(0.67)	(0.06)
BM	0.02	-0.01
	(0.32)	(0.79)
VOL	0.02	0.11
	(0.42)	(0.00)

Table 3

Estimation of the association between affect and contemporaneous stock returns

This table reports ordinary least squares regression estimation of the association between managerial affect (*PAFF* and *NAFF*) and the contemporaneous stock market reaction (*CAR(0,1)).* Superscripts HS and LS represent high scrutiny and low scrutiny partitions. $PAFF^{HS}$ ($NAFF^{HS}$) is defined as *PAFF (NAFF)* when UE_t is less than zero, and zero otherwise. $PAFF^{LS}$ ($NAFF^{LS}$) is defined as *PAFF (NAFF)* when UE_t is greater than or equal to zero, and zero otherwise. See Table 2 for detailed description for the other variables. Robust standard errors are presented in parentheses below the coefficient estimates. ***, **, * Significant at .01, .05 and .10 level, respectively, in a two-tailed test (one-tailed when predicted).

	Predicted sign	***(1)***	***(2)***
Intercept	?	-0.0108	-0.0034
		(0.0205)	(0.0200)
PAFF	+	0.1647**	
		(0.0776)	
NAFF	-	-0.0290	
		(0.0270)	
$PAFF^{HS}$	+		0.1263*
			(0.0961)
$NAFF^{HS}$	-		-0.1522***
			(0.0440)
$PAFF^{LS}$	+		0.1507**
			(0.0817)
$NAFF^{LS}$	-		0.0432
			(0.0316)
UE_t	+	0.8204***	0.2576
		(0.2494)	(0.2681)
LNMVE	?	0.0003	-0.0008
		(0.0015)	(0.0015)
MOM	?	0.0040	0.0011
		(0.0107)	(0.0104)
BM	?	-0.0037	-0.0006
		(0.0073)	(0.0071)
VOL	?	-0.1926	-0.2094
		(0.3432)	(0.3310)
POSWORDS	+	0.0290***	0.0236***
		(0.0072)	(0.0071)
NEGWORDS	-	-0.0453***	-0.0399***
		(0.0086)	(0.0085)
N		1,647	1,647
Adjusted R^2		7.64%	10.65%

Table 4
Estimation of the association between affect and analyst one quarter ahead forecast revisions

This table reports ordinary least squares regression estimation of the association between managerial affect (*PAFF* and *NAFF*) and analyst earnings forecast revisions (*FREV*) and recommendation revisions (*RECREV*). Superscripts HS and LS represent high scrutiny and low scrutiny partitions. $PAFF^{HS}$ ($NAFF^{HS}$), is defined as *PAFF (NAFF)* when UE_t is less than zero, and zero otherwise. $PAFF^{LS}$ ($NAFF^{LS}$) is defined as *PAFF (NAFF)* when UE_t is greater than or equal to zero, and zero otherwise. See Table 2 for detailed description for the other variables. Robust standard errors are presented in parentheses. ***, **, * Significant at .01, .05 and .10 level, respectively, in a two-tailed test (one-tailed when predicted).

	Predicted Sign	***FREV (1)***	***RECREV (2)***
Intercept	?	0.0022*	-0.2723***
		(0.0013)	(0.0568)
$PAFF^{HS}$	+	-0.0047	0.4200**
		(0.0076)	(0.2266)
$NAFF^{HS}$	-	0.0019	-0.0121
		(0.0036)	(0.1025)
$PAFF^{LS}$	+	0.0014	0.1056
		(0.0051)	(0.1861)
$NAFF^{LS}$	-	-0.0002	0.0862
		(0.0018)	(0.0732)
UE_t	+	0.1273***	0.9383**
		(0.0256)	(0.4967)
CAR(0,1)	+	0.0111***	0.5224***
		(0.0021)	(0.0852)
LNMVE	?	-0.0001	-0.0016
		(0.0000)	(0.0035)
MOM	?	0.0031***	0.0715***
		(0.0007)	(0.0223)
BM	?	-0.0032***	-0.0014
		(0.0007)	(0.0212)
VOL	?	-0.0834***	0.2570
		(0.0247)	(0.6596)
LAGREC	-		-0.1073***
			(0.0126)
POSWORDS	+	0.0006	-0.0148
		(0.0005)	(0.0218)
NEGWORDS	-	-0.0005	-0.0194
		(0.0007)	(0.0271)
N		1,647	1,647
Adjusted R^2		25.72%	12.06%

Table 5
Estimations of the association between affect and future earnings news

This table reports ordinary least squares regression estimation of the association between managerial affect (*PAFF* and *NAFF*) and future earnings surprises (*UE*). Superscripts HS and LS represent high scrutiny and low scrutiny partitions. $PAFF^{HS}$ ($NAFF^{HS}$), is defined as *PAFF (NAFF)* when UE_t is less than zero, and zero otherwise. $PAFF^{LS}$ ($NAFF^{LS}$) is defined as *PAFF (NAFF)* when UE_t is greater than or equal to zero, and zero otherwise. See Table 2 for detailed description for the other variables. Robust standard errors are presented in parentheses. ***, **, * Significant at .01, .05 and .10 level, respectively, in a two-tailed test (one-tailed when predicted).

	Predicted sign	UE_{t+1} ***(1)***	UE_{t+2} ***(2)***	$UE_{t+1,t+2}$ ***(3)***
Intercept	?	0.0081	0.0157**	0.0224**
		(0.0045)	(0.0068)	(0.0106)
$PAFF^{HS}$	+	0.0234	0.0690**	0.0753*
		(0.0231)	(0.0338)	(0.0510)
$NAFF^{HS}$	-	-0.0027	-0.0307**	-0.0431*
		(0.0129)	(0.0185)	(0.0294)
$PAFF^{LS}$	+	0.0107	0.0207	0.0215
		(0.0151)	(0.0223)	(0.0291)
$NAFF^{LS}$	-	-0.0056	-0.0121	-0.0192*
		(0.0053)	(0.0114)	(0.0118)
UE_t	+	0.4767***	0.4424***	0.7472***
		(0.1104)	(0.1531)	(0.2429)
FREV	+	0.4298**	0.2856	0.5811*
		(0.1878)	(0.2663)	(0.3921)
FDISP	-	-0.0357**	-0.0447*	-0.0824*
		(0.0163)	(0.0295)	(0.0521)
LNMVE	?	-0.0003	-0.0006	-0.0007
		(0.0003)	(0.0005)	(0.0008)
MOM	?	0.0078***	0.0092***	0.0123***
		(0.0028)	(0.0031)	(0.0047)
BM	?	-0.0074***	-0.0144***	-0.0211***
		(0.0023)	(0.0039)	(0.0061)
VOL	?	-0.1355	-0.3020**	-0.3334*
		(0.0977)	(0.1465)	(0.1949)
POSWORDS	+	-0.0020	-0.0022	-0.0028
		(0.0015)	(0.0018)	(0.0026)
NEGWORDS	-	0.0013	-0.0030	-0.0022
		(0.0021)	(0.0038)	(0.0053)
N		1,647	1,146	1,146
Adjusted R^2		28.80%	17.12%	20.25%

Table 6
OLS estimations of the association between affect variables and future stock returns

This table reports ordinary least squares regression estimation of the association between managerial affect (*PAFF* and *NAFF*) and future stock returns (*CAR(2,180))*. Superscripts HS and LS represent high scrutiny and low scrutiny partitions. $PAFF^{HS}$ ($NAFF^{HS}$), is defined as *PAFF (NAFF)* when UE_t is less than zero, and zero otherwise. $PAFF^{LS}$ ($NAFF^{LS}$) is defined as *PAFF (NAFF)* when UE_t is greater than or equal to zero, and zero otherwise. See Table 2 for detailed description for the other variables. Robust standard errors are presented in parentheses. ***, **, * Significant at .01, .05 and .10 level, respectively, in a two-tailed test (one-tailed when predicted).

	Predicted Sign	
Intercept	?	0.1900
		(0.1123)
$PAFF^{HS}$	+	0.5280
		(0.5649)
$NAFF^{HS}$	-	-0.6463***
		(0.2580)
$PAFF^{LS}$	+	-0.2258
		(0.4790)
$NAFF^{LS}$	-	0.0104
		(0.1697)
UE_t	+	2.2959
		(1.8075)
LNMVE	?	-0.0127
		(0.0085)
MOM	?	0.2404***
		(0.0553)
BM	?	-0.0974**
		(0.0487)
VOL	?	-3.7099*
		(1.9100)
POSWORDS	+	0.0226
		(0.0397)
NEGWORDS	-	0.0161
		(0.0476)
N		1,647
Adjusted R^2		5.39%

Table 7

Tobit estimations of the association between affect variables and proportion of bad news articles in the future

This table reports two limit tobit estimation of the association between managerial affect (*PAFF* and *NAFF*) and percentage of bad news press releases issued by the firm over the 180 days following the conference call (*PCT_BN*). *PCT_BN* is the ratio of bad news press releases issued by the firm divided by the total number of press releases issued by the firm from trading day 2 to trading day 180 after the conference call. Upper (lower) tobit limits are set at one and zero, reflecting the bounds of the percentage based dependent variable *PCT_BN.* Press releases are obtained by searching for the date of all Wire Service Stories emanating from the company's headquarters on Lexis Nexis. A press release is coded as bad if the abnormal stock return on the day of the article release (or the next trading day following the article date if the article was issued on a non-trading day or after hours) is negative. Superscripts HS and LS represent high scrutiny and low scrutiny partitions. $PAFF^{HS}$ ($NAFF^{HS}$) is defined as *PAFF (NAFF)* when UE_t is less than zero, and zero otherwise. $PAFF^{LS}$ ($NAFF^{LS}$) is defined as *PAFF (NAFF)* when UE_t is greater than or equal to zero, and zero otherwise. See Table 2 for detailed description for the other variables. Robust standard errors are presented in parentheses. ***, **, * Significant at .01, .05 and .10 level, respectively, in a two-tailed test (one-tailed when predicted).

	Predicted sign	
Intercept	?	0.5013***
		(0.0494)
$PAFF^{HS}$	-	-0.5330**
		(0.2620)
$NAFF^{HS}$	+	0.1338
		(0.1205)
$PAFF^{LS}$	-	-0.4722**
		(0.2317)
$NAFF^{LS}$	+	-0.0016
		(0.0829)
UE_t	-	0.0765
		(0.4792)
CAR(0,1)	-	-0.0289
		(0.0742)
LNMVE	?	0.0077*
		(0.0041)
MOM	?	0.0224
		(0.0221)
BM	?	-0.0095
		(0.0190)
VOL	?	-0.0415
		(0.7024)
POSWORDS	-	0.0043
		(0.0197)
NEGWORDS	+	0.0426*
		(0.0240)
N		1,304
Mean of Dependent Variable		0.506
Log Pseudoliklihood		294.34

Table 8
Investigation of analyst acknowledgement of negative affect

Panel A of this table reports two limit tobit estimation of the association between managerial affect and analyst revision activity. The dependent variable, *PCT_REV,* is the ratio of the number of analysts with outstanding upcoming annual earnings forecasts prior to the conference call who revise their estimates after the conference call. Superscripts HS and LS represent high scrutiny and low scrutiny partitions. $PAFF^{HS}$ ($NAFF^{HS}$) is defined as *PAFF (NAFF)* when UE_t is less than zero, and zero otherwise. $PAFF^{LS}$ ($NAFF^{LS}$) is defined as *PAFF (NAFF)* when UE_t is greater than or equal to zero, and zero otherwise. Panel B of this table replicates the analysis in Table 6, but allows the coefficients on affect to vary with the extent of institutional holding. High institutional holdings is an indicator variable set to one if the proportion of institutional investors in a firms stock is greater than 50%, and zero otherwise. We obtain institutional ownership from 13(f) filings during the first calendar quarter of 2007 provided the Thomson Reuters database. See Table 2 for detailed description for the other variables. Robust standard errors are presented in parentheses. ***, **, * Significant at .01, .05 and .10 level, respectively, in a two-tailed test (one-tailed when predicted).

Panel A: Two limit Tobit estimation of the association between managerial affect and forecast revision activity

	Predicted sign	
Intercept	?	0.8530***
		(0.0555)
$PAFF^{HS}$	+	0.1043
		(0.2923)
$NAFF^{HS}$	-	-0.3152**
		(0.1359)
$PAFF^{LS}$	+	-0.3551*
		(0.2363)
$NAFF^{LS}$	-	-0.1170*
		(0.0883)
UE_t	+	0.1760
		(0.5359)
CAR(0,1)	+	-0.0935*
		(0.0686)
LNMVE	?	0.0002
		(0.0043)
MOM	?	0.0402*
		(0.0250)
BM	?	-0.0594***
		(0.0229)
VOL	?	-2.7148***
		(0.8353)
POSWORDS	+	-0.0061
		(0.0222)
NEGWORDS	-	-0.0736**
		(0.0297)
N		1,647
Mean of Dependent Variable		0.704
Log Pseudoliklihood		-103.91

Panel B: OLS estimation of the association between managerial affect and future stock returns across different levels of institutional ownership

	Predicted Sign	
Intercept	?	0.1875*
		(0.1132)
$PAFF^{HS\text{-}HIghInst}$	+	0.3322
		(0.6010)
$NAFF^{HS\text{-}HIghInst}$	-	-0.5692**
		(0.3045)
$PAFF^{LS\text{-}HIghInst}$	+	-0.1815
		(0.4857)
$NAFF^{LS\text{-}HIghInst}$	-	0.0121
		(0.1579)
$PAFF^{HS\text{-}LowInst}$	+	1.2332*
		(0.9621)
$NAFF^{HS\text{-}LowInst}$	-	-0.8875**
		(0.4601)
$PAFF^{LS\text{-}LowInst}$	+	-0.4354
		(0.9091)
$NAFF^{LS\text{-}LowInst}$	-	0.0296
		(0.5144)
UE_t	+	2.4257*
		(1.8152)
LNMVE	?	-0.0128
		(0.0088)
MOM	?	0.2410***
		(0.0557)
BM	?	-0.0956**
		(0.0485)
VOL	?	-3.6571*
		(1.8703)
POSWORDS	+	0.0230
		(0.0396)
NEGWORDS	-	0.1875**
		(0.1132)
N		1,647
Adjusted R^2		5.51%