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Management deception, big-bath accounting, and information asymmetry: Evidence from linguistic analysis

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ABSTRACT

Accounting big baths are pervasive in practice. While big baths can improve the information environment and reduce information asymmetry, they can also degrade the information environment and obscure operating performance. In this study, we examine the role of management ethics. Specifically, we investigate whether managers' truthfulness (or conversely, deceptiveness) affects how investors perceive big baths. Using linguistic analysis on earnings-conference calls to measure managerial deception and employing a difference-in-differences research design with propensity-score matching, we find that information asymmetry is significantly higher following big baths taken by deceptive CEOs, compared with big baths taken by less deceptive CEOs.

1. Introduction

How does a firm's information environment change after accounting big baths? Prior literature provides evidence on both positive (Elliott & Shaw, 1988; Francis, Hanna, & Vincent, 1996; Haggard, Howe, & Lynch, 2015) and negative (Bens & Johnston, 2009; Kirschenheiter & Melumad, 2002; Kothari, Shu, and Wysocki 2009; Moore, 1973) consequences of big baths on the information environment. As managers have discretion regarding whether to incur a large write-off, and can decide the timing and amount of the write-off, management's incentives are important in studying the effects of big baths. However, such incentives are unobservable. Investors may use managerial characteristics to infer management incentives. Among the most salient managerial characteristics in this setting is truthfulness; thus this study examines how truthfulness (or conversely, deceptiveness) affects investors' perceptions of big baths.

According to upper-echelons theory (Hambrick & Mason, 1984), the ethical attentiveness throughout the organization is instilled by its leaders (Patelli & Pedrini, 2015). A series of accounting fraud scandals over the last decades put leadership ethics at the forefront of the heated debate on financial-reporting truthfulness (Mihajlov & Miller, 2012; Tourish & Vatcha, 2005). Ethics is an intrinsic part of managers' behavior (Solomon, 1992). As firms' high-level decision makers, top managers are likely to follow a cognitive and rational approach that revolves around moral judgments about the issues when making ethical decisions, just as an individual making a choice when facing an ethical dilemma (Albert, Scott, and Turan 2015; Kohlberg, 1981; Reynolds, 2006; Vitell, Lumpkin, and Rawwas 1991; Weber, 1990). Big baths are managerial decisions that can be the result of managers' ethical considerations of the firms' welfare, or can be the result of managers' incentives to maximize their personal utility. Being truthful or deceptive to investors and other stakeholders also indicates management's ethical choice of how they view their responsibility to the firm's stakeholders.

On one hand, big baths can manifest themselves as exceptionally large negative discretionary accruals. On the other hand, big baths can consist of one-time, large write-offs, and may include restructuring charges, asset impairments, and litigation losses. These write-offs are generally reflected as "special items" in the financial statements. There are two ways to look at a big bath. If a company reports a loss that is larger than expectations, it could be the case that there are certain issues within the firm that warrant such actions and that managers are truthfully conveying such information to the capital market and other stakeholders. In line with that view, some analysts interpret big baths as managers' positive response to existing problems (Elliott & Shaw, 1988). Big baths can also "clear the air" (Haggard et al., 2015). That is, by writing off assets when their carrying values are less than the market values, the reported values of the assets are realigned with their economic values. As a result, firm-level information asymmetry following a big bath should decrease.

However, big baths are sometimes used as an earning-management technique to shift current earnings to future periods. As Levitt (1998) points out, if big-bath charges are overly conservatively estimated with "extra cushioning," they can miraculously be reborn as income when future earnings fall short. Big baths can also be used to secure bonus

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payments. Often, managers' rewards are tied to meeting certain performance targets. In an economic downturn, managers may follow the big-bath approach by bundling as much bad news into the current period as possible, aiming to make their targets easier to achieve in the next period.[1] In cases of new management, big-bath accounting can be used to mitigate top executives' job-security concerns.[2] The new manager can benefit from taking a big bath, blaming the low earnings on the previous manager so as to display an improved financial performance in future (Moore, 1973).

From investors' perspectives, the action of taking big baths by a firm is observable, but the motivations behind the action are not entirely clear. Hou (2015) finds that in a well-diversified market, idiosyncratic information risk is priced when information is subject to managers' discretion and thus ambiguous. Can investors infer the motivations of managers by observing their types – truthful or deceptive – and associating their actions with the types? By taking advantage of newly-developed technologies, investors are now analyzing the linguistic patterns displayed in management speech. Investors have been using algorithmic textual analysis, CIA lie-detection techniques, and more recently, audio analysis of management speech, to seek an edge with stock calls, sector sentiment, and overall market direction.[3]

Earnings-conference calls, in which managers discuss their firms' financial performance with analysts and investors, are important information sources to search for signs of management deception. If a manager is discovered to be deceptive when discussing her firm's financial results, and the firm takes a big bath at the time, will investors perceive this big bath to have low credibility? Will investors associate this big bath with such motivations as meeting earnings targets or securing bonus payments? If this is the case, we would expect to observe an increase in information asymmetry following big baths taken by deceptive managers. Conversely, if a firm's manager takes a big bath and she is considered truthful, investors may perceive this big bath as having high credibility. In this case, the information asymmetry may decrease.

A primary reason both practicing accountants and researchers care about information asymmetry is that it reflects the information environment.[4] Clearly an important issue related to big baths is whether these accounting events improve or deteriorate the firm's information environment. However, to broaden the scope of our study, in additional analyses we also test for trading volume (another commonly employed outcome variable in this line of literature).

This study builds on Larcker and Zakolyukina (2012) who find that certain words are significantly associated with management deception. For instance, deceptive CEOs use more “reference to general knowledge” and “extreme positive emotion” words, and use fewer “anxiety” and “shareholder value” words. The linguistic approach proposed by Larcker and Zakolyukina (2012) is based on psychological theories linking deception to linguistic behavior (Vrij, 2008), and is built up by applying a well-developed and frequently used psychosocial dictionary – LIWC. There are an increasing number of applications of LIWC analyses in deception detection, and also in personality, forensic, clinical, relationship, and cultural assessments (Chung & Pennebaker, 2012, chap. 12). Providing further validity to Larcker and Zakolyukina (2012), Loughran and McDonald (2013) demonstrate that the credibility of managers is diminished by having an overly positive S-1 in the IPO process, consistent with Larcker and Zakolyukina (2012) who find that deceptive CEOs use significantly more positive emotion words in conference calls. Another piece of evidence substantiating the usefulness of CEOs’ linguistic patterns in signifying deception is provided by Hobson, Mayew, Peecher, and Venkatachalam (2017), who demonstrate that once given instructions on the “cognitive dissonance” in the CEOs remarks, auditors are able to more precisely detect fraudulent companies as well as the unidentified “red flag” sentences in earnings-conference calls.

We use Larcker and Zakolyukina (2012) approach to identify truthful and deceptive managers in this paper, and examine whether the change in information asymmetry around a big-bath event is a function of managerial deception. As CEOs play the largest role in corporate decision making, we focus on the linguistic pattern of CEOs.

In our primary analyses we employ a difference-in-differences research design coupled with propensity-score matching of treatment and control firms. This approach provides strong control for potential confounding events as well as omitted-variable biases. We find evidence that investors are able to discern managers’ deception levels from conference calls and that information asymmetry is affected accordingly. Specifically, we find that information asymmetry (proxied using Amihud, 2002 illiquidity measure and bid-ask spreads) increases significantly after big baths taken by deceptive CEOs as compared to those taken by less deceptive CEOs. In additional analyses, we find that this effect is more pronounced when a CEO who has been truthful in the past becomes deceptive in the bath year. Our inferences are robust to a variety of regression specifications and other robustness tests.

The study adds to the big-bath line of research by examining a potentially important factor that could affect the impact of big-bath taking on information asymmetry. Second, our study contributes to research on how investors use ex-ante credibility of CEOs to interpret financial reporting quality (e.g., Loughran & McDonald, 2013). We do this by applying textual-analysis techniques to accounting issues to infer management's intentions using subtle linguistic cues. Finally, the study adds to management-ethics research by examining management deception and its associated capital-market consequences in the setting of big-bath taking, an economically important event as documented in prior research.[5] This paper thus also contributes to the literature by studying the financial outcomes of CEO idiosyncratic characteristics and psychological patterns.

2. Prior literature and hypothesis development

2.1. Big-bath literature

Prior research has examined the timing, motivation for, and consequences of taking big baths. Moore (1973) finds that discretionary accounting decisions that reduce income are more likely to be made in a period of management changes. The write-offs, many of which have substantial economic consequences, reflect decisions by corporate management. Kirschenheiter and Melumad (2002) construct a theoretical model to demonstrate that managers under-report earnings the most when the news is sufficiently “bad.” Management, on average, delays the release of bad news to investors (Kothari, Shu, and Wysocki 2009). Mendenhall and Nichols (1988) find that most bad news, including large write-offs, takes place in the fourth quarter and that the market reaction for fourth-quarter bad news is smaller than the reaction to similar news in other quarters.[6]

[1] This big-bath approach is discussed in the article “why honesty is the best policy” in the special report section of The Economist, March 7, 2002.

[2] “Some new bank CEOs take an earnings bath when they start,” The Wall Street Journal, March 3, 2014.

[3] A discussion on the topic of “how to tell if a CEO is lying” can be found at http://www.CNBC.com, July 7, 2015.

[4] For example, Haggard et al. (2015) use the terms information environment and information asymmetry interchangeably.

[5] Maak and Pless (2006) call for research that focuses more on the identification and measurement of leadership styles that lead to responsible leadership. The extent to which CEOs influence accounting choices is fundamental to the understanding of how organizations work, but this linkage is poorly understood (Mackey, 2008).

[6] There are different types of write-offs. Write-offs in PP&E and inventory accounts are typically considered less reflective of earnings manipulation, while restructuring charges and write-offs of goodwill are considered more reflective of such a motif (Francis et al., 1996). Similarly, write-offs of long-lived assets after the adoption of SFAS 121 are less reflective of firms' fundamentals and such big baths are associated with managers' opportunistic actions (Riedl, 2004). Bens and Johnston (2009) find that before EITF No. 94-

On one hand, big baths can be motivated by the desire to manipulate earnings. On the other hand, big baths may be used to reflect declines in the values of assets due to poor performance, increased market competition, and changes in the economic environment. Managers can make use of big baths to turn adversity into financial advantage. Large accounting write-offs often follow CEO turnover (Murphy & Zimmerman, 1993; Strong & Meyer, 1987), as new CEOs can blame the losses taken on their predecessors and take credit for subsequent improvements in reported profitability. Not only do CEOs have incentives to maximize their bonus payments, they also wield significant influence over the firm's reported financial results and may use discretionary accruals to increase compensation or maintain their positions in firms.

However, the motivation for and consequences of big baths may not all be negative. Strong and Meyer (1987) discuss how write-down decisions may be used by managers to provide signals to investors that actions are taken to eliminate those assets generating little or no return. By cleaning up the balance sheet and reducing reported equity, a company can boost future profits and increase its per-share return. However, a series of write downs can erode investors' confidence in management and induce declines in a firm's stock price. Elliott and Shaw (1988) discuss the favorable-resolution hypothesis in which write-offs reflect managers' acknowledgement of existing problems and their constructive responses. Consistent with that view, the financial press often interprets large write-offs positively.

Christensen, Paik, and Stice (2008) examine management's motifs when faced with the opportunity of making a big bath even larger. They find that after SFAS 109, which prescribes the establishment of a deferred-tax valuation allowance when relevant, the majority of the larger-than-expected valuation allowances reflect informed management pessimism about the future of the firms, as such firms experience poorer operating performance in subsequent periods. Finally, and in a similar spirit, Haggard et al. (2015) examine the information environment of firms following large, non-recurring charges and find that earnings become smoother, firm-level information asymmetry decreases, and stock returns become more responsive to unexpected earnings.

2.2. Management ethics

CEOs are the primary decision makers within firms, and they go through a moral decision-making process and trade off costs and benefits when they face ethical choices. Several factors play a role in influencing executives' ethical behavior, such as the behavior of superiors (for CEOs this could potentially be interpreted as the board), the ethical climate of the industry, the behavior of one's equals, the lack of formal company policy, and one's personal financial needs (Baumhart, 1961; Ekin & Tezölmez, 1999).[7] Importantly, managers are given the power of discretion. In the case of high-ranking business executives, discretion to do good is also discretion to do bad (Carson, 2003). Managers often face an ethical dilemma in reporting decisions (Evans, Hannan, Krishnan, and Moser 2001; Liu, Wright, and Wu 2015). There is a social standard of ‘‘doing the right thing’’ and not acting in a deceptive, unethical manner, but at the same time, managers' incentive to maximize self-interests may lead to actions that are detrimental to the firms' stakeholders.[8]

Extant research in management emphasizes the role of the CEO as the key driver of corporate strategy (Hambrick & Mason, 1984; Zona, Minoja, and Coda 2013). “Tone at the top” not only affects corporate strategy, but also influences financial reporting choices. Amernic, Craig, and Tourish (2010) point out that a fundamental and direct manifestation of tone at the top is the narrative language of the CEO. Craig, Mortensen, and Iyer (2013) examine the linguistic features of Ramalinga Raju, the main individual involved in the biggest corporate scandal in India, and find that his word choices changed noticeably in his five annual-report letters prior to the collapse of his firm, as the scale of his financial misstatements increased. After analyzing 535 annual CEO letters to shareholders with DICTION, a computer-based language analysis program, Patelli and Pedrini (2015) find that aggressive financial reporting is associated with three thematic indicators in DICTION, namely Certainty, Realism, and Commonality.

2.3. Linguistic analysis and the conference-call literature

With technological development, investors and analysts are now able to look at both verbal and non-verbal cues that are indicative of management deception, not only from 10-Ks and 10-Qs, but also from press releases, conference calls, and other information sources. Such information has become increasingly important for investors to make decisions and for analysts to make earnings forecasts and stock recommendations.

Importantly, linguistic analysis can be applied to assess the likelihood of management deception. One stream of linguistic analysis is based on existing dictionaries or the modification of these dictionaries (also known as the “bag-of-words” approach). The most commonly used dictionaries are Harvard General Inquiry, LIWC, Diction, and Loughran and McDonald (2011). This “bag-of-words” approach, even though it does not take into account the actual and contextual meaning of words, has the advantages of being easy to understand, implement, and replicate. Subjectivity is also removed by relying on well-established dictionaries. In a well-cited study, Loughran and McDonald (2011) examine whether negative, uncertainty, and litigious words in 10-Ks can predict 10b-5 fraud lawsuits, after weighting these words to account for rarity. Using linguistic inquiry and word count (LIWC) software, Newman, Pennebaker, Berry, and Richards (2003) find a set of “lying words” that identify deceptive language in a variety of experimental settings. Most important for this study, Larcker and Zakolyukina (2012) employ LIWC as well as several self-constructed word categories to predict misstatements from linguistic features of CEO speech during quarterly earnings-conference calls.[9]

In terms of information sources to analyze management linguistic cues, conference calls have been used extensively by researchers, as these conference calls are essential in resolving the information asymmetry between firms and outside investors. Earnings-conference calls are more spontaneous than 10-Ks or 10-Qs, and the information disclosed during conference calls is mostly voluntary (Bowen, Davis, and Matsumoto 2002; Davis, Ge, and Matsumoto 2014; Frankel, Mayew, and Sun 2009; Kimbrough, 2005). Management linguistic features such as vocal emotion cues (Mayew & Venkatachalam, 2012), excessive use of negative words (Druz, Wagner, and Zeckhauser 2015), and tone dispersion (Allee & Deangelis, 2015) have been examined in prior studies and these linguistic features are demonstrated to have information content. Among practitioners, earnings-conference calls are used by equity-research firms to search for cues of deception (Javers, 2010). In addition, Auditing Standard No. 12 issued by the Public

(footnote continued)
3, when fewer codified rules existed regarding restructuring charges, managers were more likely to engage in earnings management by recognizing overly large charges.

[7] In a recent study, Cardinaels (2016) provides experimental evidence about how the interaction between a company's earnings and its information system influences the degree of honest reporting by managers.

[8] Top management is often identified as key antecedents of corporate fraud (Baucus, 1994; Chen, Cumming, Hou, and Lee 2016; Efendi, Srivastava, and Swanson 2007; Khanna, Kim, and Lu 2015).

[9] Another stream of linguistic analysis research involves supervised machine learning, such as Naïve Bayes method and Support Vector Machines. Purda and Skillicorn (2015) use a decision-tree approach to establish a rank-ordered list of words from the MD&A sections that are best able to distinguish between fraudulent and truthful reports, and use support vector machines to predict the status of each report and assign it a probability of truth.

Company Accountability Oversight Board in 2010 mandates that auditors consider "observing or reading transcripts of earnings calls" as part of the process for identifying and assessing risks of material misstatements. However, to our knowledge, no prior research has examined conference calls (or employed other textual-analysis techniques) in relation to big-bath accounting.

2.4. Hypothesis development

The research question we examine is whether big baths taken at firms with truthful CEOs are more credible, and whether investors can perceive different motivations behind big baths by looking at CEOs' linguistic cues. As CEOs possess private inside information of their firms, financial-statement users are likely to assess the credibility of management disclosure regarding the extent to which such disclosure represents management's unbiased beliefs about the true nature of the transactions and events within the firm (Hodge, Hopkins, and Pratt 2006).

Research in psychology indicates that the credibility or reputation of a source influences reactions to a message (Ciancia & Kaplan, 2010; Petty & Cacioppo, 1986; Pornpitakpan, 2004). Attribution theory illustrates that individuals have motivation to interpret and analyze events for a better understanding of the environment, and that information is gathered and combined by an individual to form a causal judgment (Riske & Taylor, 1991).

In line with the above psychological theories, Williams (1996) and Mercer (2005) find that the quality of managers' disclosures influences how the managers are judged by analysts and investors. Hodge, Hopkins, and Pratt (2006) show that the level of discretion in the reporting environment and management's reporting reputation affect the importance of incentive consistency in explaining the credibility of management disclosures. Ciancia and Kaplan (2010) argue that even for nonprofessional investors who possess limited investment expertise, these investors might still scrutinize the available information and assess the plausibility of management's disclosures.

We predict that, if CEOs are deceptive, big baths are more likely to reflect an accounting choice driven by such incentives as securing bonus payments or meeting earnings targets. Such big baths would have low credibility and should increase the firm-level information asymmetry. In contrast, a big bath taken by a less deceptive (or more truthful)CEO is more likely to be reflective of the CEO's constructive response to an existing problem or the intention to "clear the air"– realign a firm's accounting numbers with their economic values. If this is the case, big baths taken by less deceptive CEOs would have higher credibility than big baths taken by deceptive managers and should decrease information asymmetry. Conversely, the more deceptive the CEO, the less credible the big bath should be and subsequently, the higher the information asymmetry should be in the post big-bath period. Stated formally (in alternative form):

H1. *Compared with a big bath taken by a less deceptive CEO, a big bath taken by a deceptive CEO will result in an increase in the information asymmetry in the post-bath period.*

We focus on information asymmetry in our paper for two main reasons. First, information asymmetry is a fundamental issue to the health of capital markets. Addressing the effects of asymmetric information has always been on the top of the agenda for the SEC, FASB, and other regulators, as well as oversight boards. As discussed in a major conference held by SEC, the existence of asymmetric information can enable market participants to engage in deleterious strategic behaviors that would be impossible in a world of complete information. Hidden information or hidden actions may permit executives to collect unwarranted rents for themselves, at the expense of shareholders.[10] Thus, we study information asymmetry against the backdrop of big baths and management deception, in the hope of shedding light on how to prevent and mitigate the negative consequences resulting from asymmetric information in the capital markets. Second, information asymmetry has also aroused substantial interest among academic researchers. Reduction in information asymmetry, or increase in liquidity, can benefit capital markets from various perspectives. For example, Amihud and Mendelson (1986) provide theoretical and empirical evidence that higher liquidity can lower a firm's cost of capital. Supporting that prediction, Lang, Lins, and Maffett (2012) find that increased liquidity is associated with lower implied cost of capital and with higher valuation. They conclude that liquidity is a major channel through which financial reporting transparency can affect firm valuation and cost of capital.

3. Data and research design

3.1. Big baths

Identifying big-bath events is not straightforward. Generally speaking, the trade-off is between having a large enough sample that utilizes an objective (or "less subjective") approach versus the researcher using her intuition to attempt to capture the spirit of big baths by coming up with a self-constructed measure.[11] For our primary analyses we consequently employ two different empirical proxies for big baths.

For our first proxy, intuition and practical insights suggest that big baths should capture the idea that firms "over-state certain charges." We consider that firms that have *especially large* negative *discretionary* accruals would meet the definition of "over-stating charges." Specifically, we employ the performance-adjusted version of Kothari, Leone, and Wasley's discretionary accruals model. We require industry-year adjusted income before extraordinary items minus special items to be in the bottom tercile and we require performance-matched discretionary accruals to be in the bottom quintile of the distribution. Please see Appendix A for further details. Consequently, this measure – "the Accruals Approach" - should capture especially egregious charges that are likely to fall under the caption of big baths. However, this comes at the cost of a relatively small sample size (resulting from our matched-sample design described below).

As our second approach, we follow a more objective approach that allows us to benchmark our results on recent research (Haggard et al., 2015). Specifically, we identify big baths as fiscal year-end observations in Compustat for which Special Items are negative and exceed one percent of lagged total assets (i.e., they are *especially large and non-recurring charges*). This definition is consistent with prior research including Elliott and Shaw (1988) and Haggard et al. (2015). We name this approach as the "Special Items Approach" for future discussion. Appendix A provides a detailed description of what goes into the "Special Items Approach."

Considering the research design and the availability of earnings-conference calls, we choose 2005 to 2015 as the sample period to define big baths, generate treatment baths, and perform propensity-score matching.[12] From this sample, we remove financial firms (SIC codes

[10] Excerpts of the keynote address by Mark J. Flannery, the chief economist and director of Division of Economic and Risk Analysis at SEC, in a 2015 conference on auditing and capital markets.

[11] Not surprisingly, researchers have employed a variety of empirical approaches. Definitions of big baths include announced asset write-downs (Francis et al., 1996; Strong & Meyer, 1987) and non-discretionary asset write-downs (Elliott & Shaw, 1988). However, these definitions of big baths suffer from certain limitations. For example, only focusing on announced asset write-downs ignores multiple small write-downs that do not warrant disclosure individually, but can be substantial when combined together; manual deletion of non-discretionary items can introduce subjectivity (and thus measurement error) into the sample selection (Haggard et al., 2015).

[12] Quarterly conference-call transcripts are obtained from SeekingAlpha.com. We start

between 6000 and 6199), firms with total assets less than five million dollars, and firms with the absolute value of Special Items exceeding 100 percent of total assets. A big-bath indicator is generated that equals one for each big bath identified satisfying our definition, zero otherwise. There are 4557 such cases under the Accruals Approach, and 14,209 under the Special Items Approach. To cleanly analyze how the information asymmetry changes from the pre to post period, baths are removed that occur within one year of another bath, both before and after, to avoid complications arising from multiple consecutive baths. A total of 3180 unique treatment baths are identified under the Accruals Approach and 6174 are identified under the Special Items Approach.

To test how the market reacts, we use two event windows in the empirical analyses: three and six months pre and post baths.[13] To create a benchmark sample, event windows for the control group are also generated in a similar way. The control group consists of firms that did not take any bath during the period of 2005–2015. Through propensity-score matching (see below), each treatment bath firm is matched to a control firm that does not take a big bath in the event window. We comment on alternative matching approaches as well as non-matching based tests in Section 5.1.1.

3.2. Management deception

Larcker and Zakolyukina (2012) propose a linguistic approach that can be used to detect management deceptive discussions during earnings-conference calls. They find that deceptive managers' speech displays certain linguistic patterns. In this paper, we apply their methodology to identify whether CEOs are classified as high or low in terms of deceptiveness. A summary of the linguistic approach in Larcker and Zakolyukina (2012) is provided in Appendix B.

To apply Larcker and Zakolyukina (2012) approach to our setting, we first need to obtain earnings conference-call transcripts for linguistic analysis. Specifically, we use Python to crawl the website http://seekingalpha.com/earnings/earnings-call-transcripts. SeekingAlpha.com is a crowd-sourced content service for financial markets. SeekingAlpha.com is also used by Allee and Deangelis (2015) as their source for collecting such transcripts.

A typical conference-call transcript can be divided into three parts. Basic information is listed in the first part: company name, ticker symbol, fiscal year, quarter, transcript date, and a list of inside and outside participants with their names and occupations. We use Python to extract the basic information.

The second part is management prepared remarks. Following the operator's introduction, the CEO will discuss the financial situation, financial performance, and other major events or changes during the period covered by the conference call. The third part is the question and answer session (Q&A), in which analysts ask questions for managers to answer. To some extent, the prepared remarks section is more scripted than the Q&A section. However, Larcker and Zakolyukina (2012) find similar results in their linguistic models regardless of pooling these two sections together or separating them. As combining these two sections provides more instances of words to analyze, we follow Larcker and Zakolyukina (2012) and do not make a distinction between the prepared remarks and Q&A. As an additional test, we also run tests using linguistic patterns displayed in prepared remarks and Q&A, separately, to identify management deception. The test results are discussed in section 5.2.

All phrases that belong to a CEO in the conference calls are gathered for linguistic analysis. The transcripts are structured in the chronological order of the speech: each speaker's name is followed by the content of her speech, and then the next speaker's name and her speech. For each transcript, we use Python to collect all the parts of the speech that belongs to the same speaker, so that the content of each transcript is classified and allocated to different speakers. Next, we pick the speech of CEOs from the classified transcripts and combine CEO speech with company name, ticker symbol, fiscal year, quarter, and transcript date, constructing a dataset that can be linked with Compustat through ticker symbols.

Larcker and Zakolyukina (2012) use the Linguistic Inquiry and Word Count psychosocial dictionary (LIWC) for their textual analysis (see also Pennebaker, Chung, Ireland, Gonzales, and Booth 2007). They construct several word categories based on their readings of the conference-call transcripts. To be consistent with Larcker and Zakolyukina (2012), we use LIWC 2007 software to count the word frequency for each word category.[14]

Larcker and Zakolyukina (2012) build linguistic models by regressing accounting irregularities or restatements on word frequencies as well as total word count. They find that deceptive CEOs use more “reference to general knowledge” and “extreme positive emotion” words, and use fewer “anxiety” and “shareholder-value” words. We provide details of deceptive words in Appendix C.

We calculate aggregated deception scores that indicate the tendency of managers to be deceptive. First, for each category of deceptive words, we calculate the sample-median word frequency and code a score of 2 (1) if a CEO is associated with an above (equal to or below) sample-median word frequency. Word frequencies are multiplied by minus one for words that are negatively associated with deception. Then we add up the scores of each word category to generate a total deception score. The score is further standardized so that the range of the variable remains between zero and one. If a firm has a deception score that is above (equal to or below) the sample median of the deception score, we classify the firm into the high (low) deception group. The indicator variable *DECEPTION* equals one for the CEOs who are classified to the high deception group, zero otherwise.

3.3. Propensity-score matching

When analyzing changes in information asymmetry between the pre- and post-bath periods, it is important to control for non-bath events. For example, big baths are generally associated with negative income in the pre-bath period, and it is possible that changes in information asymmetry are common among firms with poor operating performance. Failing to control for such factors would introduce an omitted-variable bias into the regression model. It is also essential to control for the potential firm characteristics that are associated with a firm's big-bath taking choice. In order to mitigate such endogeneity concerns and isolate the effect of big baths, we use a difference-in-differences approach and in particular employ propensity-score matching to match treatment firms and control firms. Propensity-score matching enhances the comparability between treatment firms and control firms, as the propensity score summarizes across all relevant matching variables and offers a diagnostic on the comparability of the treatment and comparison groups (Dehejia & Wahba, 1999).

Each treatment firm is matched to a control firm using propensity-score matching. To generate propensity scores, we run logit regressions, for both the Accruals Approach and Special Items Approach, with the big-bath indicator as the dependent variable and with firm size, book-to-market ratio, net income scaled by total assets, revenue scaled by total assets, annual cumulative stock returns, annual Amihud illiquidity, annual share turnover, leverage, sales growth, institutional ownership, and analyst coverage as explanatory variables.[15] Treatment

(*footnote continued*)
the sample period in 2005 as this is when the website provides sufficient conference-call transcripts.

[13] In choosing the event window, the trade-off is between isolating the effect (i.e., using a short window) versus investors having sufficient time to respond (i.e., using a longer window).

[14] We remove CEOs with fewer than 150 total word counts from the sample.

[15] Among these matching variables, following Francis et al. (1996) and Haggard et al.

baths with missing data points on the matching variables are dropped after this stage. Treatment baths with no conference-call data available are also dropped, resulting in 327 treatment baths under the Accruals Approach and 1137 treatment baths under the Special Items Approach for the next step in which each treatment firm is matched to a control firm that has the same industry classification, the same fiscal-year end, and the closest propensity score. The control group consists of firms that have not taken any bath during the sample period. A total of 254 treatment firms are matched to 254 control firms in the Accruals Approach; 442 treatment firms are matched to 442 control firms in the Special Items Approach.

We employ nearest-neighbor matching without replacement. A caliper is imposed in the matching process, as involving caliper is generally a best practice to decrease the likelihood of "poor" matches and to improve covariate balance (Shipman, Swanquist, and Whited 2017). For each successful match, the maximum allowable distance between propensity scores is restricted within the range of a caliper distance. A better covariate balance can be achieved following this approach, but it may come at the cost of a reduced sample size. We set a strict caliper distance of 0.00001 for the propensity-score matching procedure for both the Accruals Approach and Special Items Approach, as in this way a matched treatment and control group that are comparable across many important matching variables can be generated, without unduly reducing the sample size.

3.4. Difference-in-differences approach and research model

We use the following model to test our hypothesis:

$$IA = \alpha + \beta_1\, TREAT + \beta_2\, POST + \beta_3\, DECEPTION + \beta_4\, TREAT \times POST + \beta_5\, TREAT \times DECEPTION + \beta_6\, POST \times DECEPTION + \beta_7\, TREAT \times POST \times DECEPTION + \delta\, \text{Controls} + \text{Year Fixed Effects} + \text{Industry Fixed Effects} + \varepsilon$$

We use a difference-in-differences research design to examine whether CEOs being truthful can increase the credibility of big baths and whether investors can perceive the different motivations behind big baths taken by the two types of CEOs. In the model, *TREAT* equals one for firms in the treatment bath group and zero for firms in the control group. *POST* is an indicator variable that equals one (zero) for the months after (prior to) a bath. *DECEPTION* equals one for CEOs that belong to the high-deception group. The main variable of interest is β_7, which measures the difference between the high- and low-deception groups in terms of the changes in information asymmetry post bath. We use this triple-difference framework to study whether the effects of big baths on information asymmetry differ for baths taken by more deceptive CEOs versus those taken by less deceptive CEOs.

The dependent variable is information asymmetry (IA), as captured by Amihud (2002) illiquidity measure and bid-ask spreads, both of which are widely used in the literature (e.g., Balakrishnan, Billings, Kelly, and Ljungqvist 2014; Haggard et al., 2015). Goyenko, Holden, and Trzcinka (2009) conclude that the Amihud measure is better at capturing price impact than other liquidity measures. *Amihud* is defined as the monthly mean of the daily absolute returns divided by dollar volume. In the regressions, we take the log of one plus Amihud. *Spread* is defined as the monthly average of the daily bid-ask spreads. Data used to calculate the liquidity measures are obtained from the CRSP daily profile.

Our differences-in-differences approach controls for time-invariant determinants of information asymmetry. However, to reduce the possibility that our findings are confounded by omitted variables, we include a number of control variables that are motivated by prior research. The control variables include SIZE (log of total assets), BTM (book-to-market ratio), INCOME (income scaled by total assets), LEVERAGE (debt to equity ratio), RETURN_A_LAG (lagged annual return), INSTOWN (institutional ownership), ANALYST (analyst coverage), EARNING_SHOCK (absolute value of earnings shock), ROA_CHANGE (change in ROA), BEAT (indicator variable of beating analyst forecast), DELTA (CEO equity compensation delta), VEGA (CEO equity compensation vega), DELTA_M and VEGA_M (indicator variables of whether CEO delta or vega is missing), GENKNLREF_PRIOR, POSEMOEXTR_PRIOR, SHVALUE_PRIOR, and ANX_PRIOR (CEO prior linguistic patterns). SIZE, MTB, INCOME, LEVERAGE, INSTOWN, and ANALYST are firm characteristics shown to be associated with information asymmetry in prior literature. Studies find that firm size is negatively associated with percentage spread (Glosten & Harris, 1988; Leuz, 2003) and PIN (Brown, Hillegeist, & Lo, 2004). We therefore expect a negative coefficient on SIZE. INSTOWN is used to control for the presence of potentially informed market participants and sophisticated investors (Brown et al. 2004). We expect a negative coefficient on INSTOWN, given prior literature illustrates a negative association between information asymmetry and the percentage of institutional ownership (Bhattacharya, Desai, & Venkataraman, 2013). Analyst following can reflect the information collection process of market participants and its interaction with firms' financial reporting practice (Bhushan, 1989). Firms with higher analyst following are found to be associated with lower information asymmetry (Bhattacharya et al., 2013), and with reduced profitability of insider trades (Frankel & Li, 2004). We expect the coefficient on ANALYST to be negative. BEAT is a measure indicating whether a firm's actual earning exceeds analysts' consensus forecast by a small margin. Brown, Hillegeist, and Lo (2009) find that "beat" firms experience a decrease in information asymmetry. Thus, we expect a negative coefficient on BEAT.

We add several other measures in our regression model to control for their potential influential effects, but do not provide a directional prediction on these coefficients due to the lack of consensus findings in prior research. BTM, book to market ratio, is a proxy for growth opportunities or risk. Information asymmetry and disclosure issues are pertinent for growth firms, generally characterizing by a high level of intangible assets (Leuz, 2003; Smith & Watts, 1992). However, analyst coverage is also higher for such firms and analysts expend more effort in analyzing these firms. In terms of LEVARAGE, pecking order theory of capital structure implies that leverage is negatively associated with the amount of firm-investor information asymmetry. However, the incentive for private information acquisition is demonstrated to be increasing with leverage (Boot & Thakor, 1993). EARNING_SHOCK, the absolute value of earnings shock, controls for the information content of the earnings announcement (Bushee, Core, Guay and Hamm 2010). INCOME, RETURN_A_LAG, and ROA_CHANGE are added to control for firms' financial performance, as prior studies show that the level of firm investor information asymmetry is likely to increase with performance variability (Brown & Hillegeist, 2007). We also control for CEO risk taking incentives, measured by DELTA, the sensitivity of a manager's wealth to the firm's stock price, and VEGA, the sensitivity of a manager's wealth to the firm's stock return volatility. CEO DELTA and VEGA are found to be significantly associated with firms' financial policies such as corporate leverage and cash holding policies. GENKNLREF_PRIOR, POSEMOEXTR_PRIOR, SHVALUE_PRIOR, and ANX_PRIOR represent prior conference calls' average word frequencies in the use of "reference to general knowledge," "extreme positive emotions," shareholder value," and "anxiety." These variables are included in the regressions to control for the effect of the CEO's linguistic habit.[16] All

(*footnote continued*)
(2015), size, book-to-market ratio, net income scaled by total assets, revenue scaled by total assets, annual cumulative stock returns, annual Amihud illiquidity, and annual share turnover are lag values. Leverage, sales growth, institutional ownership, and analyst coverage are current-year observations.

[16] Results are robust if we remove these four linguistic characters as control variables. More generally, our inferences are not affected by the inclusion or exclusion of particular control variables.

continuous variables are winsorized at the 1st and 99th percentiles. Finally, we include both year and industry fixed effects (based on two-digit SIC codes) and cluster the standard errors by firm.[17]

We use the Compustat variable Datadate, which indicates the fiscal-year end for the financial statements, to identify the cutoff for the pre and post periods. The advantage of using Datadate is that it is consistently available across firm years and is closely associated with how we define big baths. Each Datadate is matched with the most recent earnings-conference call held prior to this Datadate. We further require that the time lag between a conference call and Datadate to be within one year. By doing so, we intend to capture investors' perceptions of CEO deception most related to the fiscal-year end big baths. The choice is also consistent with the recency effect in psychology – people tend to recall things that arrive more recently (or appear at the end of a list).[18]

4. Empirical results

4.1. Sample selection and effectiveness of propensity-score matching

Table 1 presents the sample-selection process for the final treatment firms. Table 2 exhibits the logistic regression of the big-bath indicator on important predictors of such big baths.[19] Of all the matching variables used in the propensity-score matching under the Accruals Approach in defining big baths, BTM_LAG (lag of book to market ratio), TURNOVER_A_LAG (lag of annual share turnover), LEVERAGE, and ANALYST are positively associated with big baths and the coefficients are statistically significant (0.136, 0.0672, 0.177, 0.138, respectively). SIZE_LAG, REVENUE_LAG, INCOME_LAG, RETURN_A_LAG, AMIHUD_A_LAG, SALEGROWTH, and INSTOWN are negatively associated with big baths and the coefficients are statistically significant (−0.361, −0.0775, −2.473, −0.0851, −0.0926, −0.148, and −0.424, respectively). For the Special Items Approach in defining big baths, the logit regression shows that SIZE_LAG, BTM_LAG, REVENUE_LAG, TURNOVER_A_LAG, LEVERAGE, and INSTOWN (INCOME_LAG, RETURN_A_LAG, AMIHUD_A_LAG, SALEGROWTH, and ANALYST) are positively (negatively) related to big baths.

Table 3 reports the summary statistics of the main variables of the treatment and control firms. Table 4 presents the results of the differences in these variables across the treatment and control groups. After propensity-score matching, there is considerable similarity between bath and non-bath firms. Panel A illustrates the results of key variable difference after propensity-score matching under the Accruals Approach. After propensity-score matching, only INCOME_LAG remains significantly different between treatment and control firms, according to *t*-test results. REVENUE_LAG, INCOME_LAG, and SALEGROWTH remain significant between treatment and control firms, based on Kolmogorov-Smirnov (K-S) test. Panel B demonstrates the results of variable difference after propensity-score matching under the Special Items Approach. REVENUE_LAG, INCOME_LAG, RETURN_A_LAG, and Amihud_A_LAG remain different in the *t*-test; BTM_LAG, REVENUE_LAG, and LEVERAGE are different in the K-S test. Table 5 illustrates the correlations among key variables for the main regressions under the Accruals Approach.

Table 1
Propensity-score matching sample selection.

	Accruals Approach	Special Items Approach
Bath identified	4557	14,209
Treatment bath identified	3180	6174
Treatment bath with propensity score	1198	3324
Treatment bath with conference call data	327	1137
Treatment bath after propensity-score matching	254	442

This table illustrates how the sample size for treatment baths changes after propensity-score matching.

Table 2
Propensity-score matching logit regression.

Variables	(1) Accruals Approach	(2) Special Items Approach
	Bath	Bath
SIZE_LAG	−0.361***	0.0964***
	(-16.67)	(9.463)
BTM_LAG	0.136***	0.103***
	(3.438)	(3.938)
REVENUE_LAG	−0.0775*	0.220***
	(-1.787)	(8.057)
INCOME_LAG	−2.473***	−1.157***
	(-23.02)	(-14.67)
RETURN_A_LAG	−0.0851*	−0.212***
	(-1.677)	(-7.391)
TURNOVER_A_LAG	0.0672***	0.0270***
	(5.956)	(3.767)
AMIHUD_A_LAG	−0.0926***	−0.0958***
	(-2.675)	(-4.137)
LEVERAGE	0.177***	0.142***
	(11.68)	(13.16)
SALEGROWTH	−0.148***	−0.0788**
	(-2.917)	(-2.439)
INSTOWN	−0.424***	0.504***
	(-4.127)	(10.07)
ANALYST	0.138***	−0.129***
	(3.773)	(-6.791)
Observations	33,585	32,854
Industry FE	Yes	Yes
Year FE	Yes	Yes
ROC	82.36%	70.76%
Pseudo R^2	0.163	0.0959

This table represents results of logit regressions for propensity-score matching, under both the Accruals Approach and Special Items Approach. Dependent variable is the big bath indicator. Explanatory variables include lag value of SIZE (log of total assets), BTM (book to market ratio), REVENUE (revenue scaled by total assets), INCOME (net income scaled by total assets), RETURN_A (annual return), TURNOVER_A (annual turnover), and AMIHUD_A (annual Amihud); explanatory variables also include LEVERAGE (leverage), SALEGROWTH (sales growth year over year), INSTOWN (institutional ownership), ANALYST (analyst coverage). Industry fixed effects and year fixed effects are included. ROC represents the area under the ROC curve. Z-statistics in parentheses ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

4.2. Main tests

Table 6 presents the results of different specifications of regressions testing how information asymmetry changes after big baths taken by deceptive CEOs, compared with big baths taken by less deceptive CEOs. *AMIHUD* and *SPREAD* are the dependent variables. Panel A represents results from the Accruals Approach and Panel B represents results from the Special Items Approach. The main variable of interest is the coefficient on the interaction term $TREAT \times POST \times DECEPTION$. We report results with 3 month and 6 month as event-window lengths.

In Panel A, the dependent variable is *AMIHUD* in columns 1 and 2,

[17] Alternatively, we cluster standard errors by industry instead of by firm. No conclusions are affected (untabulated).

[18] Each big-bath event is associated with CEO linguistic characteristics identified in the most recent earnings conference call prior to the fiscal year-end. To illustrate the timeline of the overall research design, if a firm has a year-end of December 31, 2017 (Datadate), the associated conference call date could be October 2017, which is the conference call held closest to the year-end date. We then calculate the information asymmetry and trading volume measures for each month from December 2016 to November 2018.

[19] The area under the curve is 82.36% (70.76%) for the Accruals Method (Special Items Method).

Table 3
Panel A: Descriptive statistics – accruals approach.

Treat	Variable	Mean	SD	P25	P50	P75
0	SIZE	6.09	1.59	4.94	5.94	7.13
	BTM	0.71	0.76	0.28	0.52	0.98
	INCOME	−0.06	0.20	−0.12	0.01	0.06
	RETURN_A_LAG	0.02	0.52	−0.35	−0.01	0.26
	LEVERAGE	0.93	1.87	0.00	0.18	0.78
	SALEGROWTH	0.13	0.49	−0.08	0.06	0.22
	INSTOWN	0.54	0.38	0.21	0.57	0.88
	ANALYST	2.06	0.99	1.79	2.25	2.71
	GENKNLREF	0.05	0.08	0.00	0.03	0.07
	POSEMOEXTR	0.70	0.34	0.46	0.64	0.90
	SHVALUE	0.01	0.03	0.00	0.00	0.00
	ANX	0.10	0.12	0.00	0.06	0.13
1	SIZE	6.22	1.77	4.90	6.07	7.50
	BTM	0.54	0.72	0.16	0.45	0.82
	INCOME	−0.23	0.25	−0.33	−0.13	−0.06
	RETURN_A_LAG	0.00	0.53	−0.33	−0.07	0.20
	LEVERAGE	0.91	1.75	0.01	0.21	0.85
	SALEGROWTH	0.08	0.48	−0.15	0.01	0.23
	INSTOWN	0.55	0.39	0.20	0.58	0.87
	ANALYST	2.05	1.16	1.39	2.30	2.89
	GENKNLREF	0.05	0.08	0.00	0.02	0.07
	POSEMOEXTR	0.75	0.36	0.50	0.71	0.94
	SHVALUE	0.01	0.03	0.00	0.00	0.00
	ANX	0.10	0.12	0.00	0.07	0.15

This table exhibits descriptive statistics, under the Accruals Approach, of key variables in the bath-year (or matched year for non-bath group) for the final sample after propensity-score matching. Descriptive statistics for control and treatment group are displayed separately in the top and bottom half of the table. Variables listed include SIZE (log of total assets), BTM (book to market ratio), INCOME (net income scaled by total assets), RETURN_A_LAG (lag of annual return), LEVERAGE (leverage), SALEGROWTH (sales growth year over year), INSTOWN (institutional ownership), and ANALYST (analyst coverage). Also listed are descriptive statistics of word frequencies for deceptive words GenKnlRef (reference to general knowledge), PosEmoExtr (extreme positive emotions), ShareValue (shareholder value), and ANX (anxiety).

Table 3
Panel B: Descriptive statistics – special items approach.

Treat	Variable	Mean	SD	P25	P50	P75
0	SIZE	7.16	2.16	5.55	7.21	8.60
	BTM	0.49	0.50	0.19	0.37	0.63
	INCOME	−0.01	0.23	0.00	0.04	0.09
	RETURN_A_LAG	0.25	0.54	−0.06	0.15	0.43
	LEVERAGE	0.45	1.07	0.00	0.11	0.50
	SALEGROWTH	0.17	0.43	0.00	0.09	0.22
	INSTOWN	0.64	0.37	0.32	0.72	0.94
	ANALYST	2.38	1.09	1.95	2.48	3.26
	GENKNLREF	0.06	0.11	0.00	0.03	0.08
	POSEMOEXTR	0.75	0.41	0.47	0.66	0.94
	SHVALUE	0.01	0.03	0.00	0.00	0.00
	ANX	0.11	0.12	0.00	0.08	0.16
1	SIZE	7.26	1.99	5.80	7.19	8.56
	BTM	0.54	0.49	0.25	0.44	0.72
	INCOME	−0.02	0.16	−0.05	0.02	0.06
	RETURN_A_LAG	0.31	0.56	−0.04	0.19	0.51
	LEVERAGE	0.48	0.85	0.04	0.22	0.59
	SALEGROWTH	0.17	0.43	0.00	0.09	0.21
	INSTOWN	0.65	0.37	0.40	0.75	0.95
	ANALYST	2.34	1.11	1.95	2.64	3.14
	GENKNLREF	0.05	0.09	0.00	0.03	0.07
	POSEMOEXTR	0.74	0.36	0.51	0.70	0.93
	SHVALUE	0.01	0.04	0.00	0.00	0.00
	ANX	0.10	0.12	0.00	0.07	0.15

This table exhibits descriptive statistics, under the Special Items Approach, of key variables in the bath-year (or matched year for non-bath group) for the final sample after propensity-score matching. Descriptive statistics for control and treatment group are displayed separately in the top and bottom half of the table. Variables listed include SIZE (log of total assets), BTM (book to market ratio), INCOME (net income scaled by total assets), RETURN_A_LAG (lag of annual return), LEVERAGE (leverage), SALEGROWTH (sales growth year over year), INSTOWN (institutional ownership), and ANALYST (analyst coverage). Also listed are descriptive statistics of word frequencies for deceptive words GenKnlRef (reference to general knowledge), PosEmoExtr (extreme positive emotions), ShareValue (shareholder value), and ANX (anxiety).

and *SPREAD* in columns 3 and 4. The estimated coefficients on *TREAT×POST×DECEPTION* are all positive and statistically significant (at the 5% level or better using two-sided tests). Specifically, the coefficients are 0.0957, 0.105, 0.196, and 0.191. Consistent with our hypothesis, Panel A shows that big baths taken by deceptive managers lead to significant increase in information asymmetry after big baths, compared with big baths taken by less deceptive managers.[20]

For control variables, the signs on the variables are mostly consistent with prior literature. SIZE, RETURN_A_LAG, and INSTOWN are negatively associated with information asymmetry and statistically significant. BTM, LEVERAGE, and ROA_CHANGE are positively associated with information asymmetry.

Using the larger sample but likely coarser measure of big baths in Panel B, again the estimated coefficients on *TREAT×POST×DECEPTION* are all positive and statistically significant. Thus, our inferences are consistent using an alternative

Table 4
Panel A: Variable differences after propensity-score matching - accruals approach.

Matching Variable	Difference	T-test (P-value)	K-S (P-value)
SIZE_LAG	−0.15	0.34	0.11
BTM_LAG	0.07	0.23	0.14
REVENUE_LAG	0.03	0.61	0.09
INCOME_LAG	0.06	0.00	0.00
RETURN_A_LAG	0.02	0.67	0.25
TURNOVER_A_LAG	−0.12	0.63	0.14
AMIHUD_A_LAG	−0.01	0.84	0.62
LEVERAGE	0.02	0.91	0.14
SALEGROWTH	0.05	0.23	0.04
INSTOWN	0.00	0.95	1.00
ANALYST	0.01	0.90	0.37
PROPENSITY-SCORE	0.00	1.00	1.00

This table illustrates the difference of key matching variables between treatment group and control group after propensity-score matching, for the Accruals Approach. Matching variables include lag value of SIZE (log of total assets), BTM (book to market ratio), REVENUE (revenue scaled by total assets), INCOME (net income scaled by total assets), RETURN_A (annual return), TURNOVER_A (annual turnover), and AMIHUD_A (annual Amihud); key matching variables also include LEVERAGE (leverage), SALEGROWTH (sales growth year over year), INSTOWN (institutional ownership), ANALYST (analyst coverage). The difference in propensity-score is also provided. In testing the difference of these matching variables between treatment and control group, *t*-test and Kolmogorov-Smirnov test are performed, with p-values provided in the table.

[20] The primary coefficients of interest, in the triple-interaction specification, are the coefficients on *TREAT × POST* and especially *TREAT × POST × DECEPTION*. The coefficient on *TREAT × POST* captures the net effect of big baths for less deceptive CEOs; the coefficient on *TREAT × POST × DECEPTION* measures the differential effect of big baths for deceptive CEOs, compared with less deceptive CEOs. From Panel A, we observe that coefficients on *TREAT × POST* are negative through column 1 to column 4 (statistically significant for column 2, 3, and 4), indicating that information asymmetry decreases, or information environment improves, post big baths for less deceptive CEO group. The coefficients on *TREAT × POST × DECEPTION* are positive and statistically significant in all columns, indicating that information asymmetry increases, or information environment worsen off, if the baths are taken by deceptive CEOs. In terms of numerical magnitude, using regression result in column 1 to illustrate, the net effect of big baths on information asymmetry for less deceptive CEO is − 0.0311, while the net effect of big baths on information asymmetry for deceptive CEO is 0.0646 (− 0.0311 + 0.0957). We find consistent results in Panel B, in which big baths are identified using special items. As an alternative approach to avoid the three-way interaction, we estimate our model including *TREAT*, *POST*, and *TREAT×POST* in separate deceptive and less-deceptive subsample regressions. In untabulated results, the coefficients on *TREAT×POST* are all significantly positive in regressions for deceptive CEOs, whether using three month or six month as event window, or with Amihud or Spread as information asymmetry measure. In contrast, the coefficients on *TREAT×POST* are negative in regressions for less deceptive CEOs. The difference in coefficients on *TREAT×POST* between deceptive and less deceptive subgroups is positive and statistically significant, according to a z-test (Paternoster, Brame, Mazerolle, and Piquero 1998). Overall, this approach provides consistent evidence that information asymmetry increases after big baths taken by deceptive CEOs.

Table 4
Panel B: Variable differences after PSM - special items approach.

Matching Variable	Difference	T-test (P-value)	K-S (P-value)
SIZE_LAG	−0.04	0.78	0.53
BTM_LAG	0.00	0.97	0.08
REVENUE_LAG	−0.13	0.01	0.00
INCOME_LAG	−0.03	0.01	0.23
RETURN_A_LAG	−0.06	0.08	0.26
TURNOVER_A_LAG	0.01	0.93	0.17
AMIHUD_A_LAG	−0.05	0.06	0.86
LEVERAGE	−0.03	0.65	0.00
SALEGROWTH	0.00	0.93	0.81
INSTOWN	−0.01	0.69	0.64
ANALYST	0.04	0.62	0.34
PROPENSITY-SCORE	0.00	1.00	1.00

This table illustrates the difference of key matching variables between treatment group and control group after propensity-score matching, for the Special Items Approach. Matching variables include lag value of SIZE (log of total assets), BTM (book to market ratio), REVENUE (revenue scaled by total assets), INCOME (net income scaled by total assets), RETURN_A (annual return), TURNOVER_A (annual turnover), and AMIHUD_A (annual Amihud); key matching variables also include LEVERAGE (leverage), SALEGROWTH (sales growth year over year), INSTOWN (institutional ownership), ANALYST (analyst coverage). The difference in propensity-score is also provided. In testing the difference of these matching variables between treatment and control group, *t*-test and Kolmogorov-Smirnov test are performed, with p-values provided in the table.

research-design choices. For brevity, we do not tabulate the results of all these analyses.

5.1.1. Sensitivity analyses related to matching

As described in Section 4.1, only one variable is statistically different (based on a *t*-test) between the treatment and control samples after our propensity-score matching approach when using the Accruals Approach. For the Special Items - based big-bath definition, four variables remain significantly different. This reflects a trade-off between reducing differences between the two samples and having a sufficiently large sample ("generalizability"). Please note that we include the matching dimensions as control variables in all tests. To assess the robustness of our findings to our propensity-score matching specifications, we conduct the following tests. First, for the variables with significant differences after matching, we include non-linear terms in the regression tests. Specifically, we include either the square root or the squared of these variables as additional regressors and find that conclusions are unchanged.

Next, we implement a different matching approach: *entropy matching*. This approach allows the researcher to match not only on means but also on higher-order dimensions of the covariates. We find that our results continue to hold. Finally, although we believe the propensity-score matching approach provides strong control for potential omitted variables, to generalize our findings we run the regression *without* a control sample and thus test for a pure pre-post effect for the treated firms. This sensitivity test also ensures that our findings are not induced by matching (i.e., are not driven solely by the control-sample firms). Again, inferences remain. In sum, our findings are not sensitive to our PSM choices.

Table 5
Pearson correlation table – accruals approach.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
AMIHUD_M (1)																
SPREAD_M (2)	**0.87**															
TREAT (3)	0.02	**0.04**														
POST (4)	0.00	0.01	0.00													
DECEPTION (5)	−0.01	−0.01	0.02	0.00												
SIZE (6)	**−0.39**	**−0.48**	**0.03**	0.00	**−0.03**											
BTM (7)	**0.12**	**0.14**	**−0.11**	**−0.05**	**−0.03**	**0.00**										
INCOME (8)	**−0.08**	**−0.16**	**−0.33**	**0.11**	**0.12**	**0.34**	**0.11**									
LEVERAGE (9)	**0.02**	**0.04**	−0.01	−0.02	**−0.09**	**0.33**	**−0.11**	**0.04**								
RETURN_A_LAG (10)	**−0.12**	**−0.17**	−0.02	0.00	**0.04**	**0.03**	**−0.10**	**0.08**	**−0.11**							
INSTOWN (11)	**−0.28**	**−0.38**	0.01	−0.01	**0.05**	**0.29**	**−0.13**	**0.13**	**−0.11**	**0.14**						
ANALYST (12)	**−0.35**	**−0.44**	−0.01	0.01	**0.03**	**0.44**	**−0.17**	**0.11**	**−0.06**	**0.07**	**0.63**					
EARNING_SHOCK (13)	**−0.08**	**−0.09**	**0.10**	**−0.09**	**−0.06**	**0.26**	**−0.03**	**0.03**	**0.27**	−0.01	**0.12**	**0.20**				
ROA_CHANGE (14)	**0.10**	**0.10**	**−0.07**	0.00	**0.02**	**−0.11**	**−0.02**	**0.02**	**−0.03**	0.02	−0.01	**−0.04**	**−0.03**			
BEAT (15)	**−0.03**	**−0.04**	**−0.03**	−0.01	−0.01	−0.02	**−0.02**	**0.04**	**−0.05**	**0.03**	**0.05**	**0.04**	**−0.05**	**0.03**		
DELTA (16)	**−0.05**	**−0.06**	**−0.09**	0.00	**0.09**	**−0.07**	**−0.07**	**0.11**	**−0.09**	**0.09**	**0.11**	**0.03**	**−0.05**	0.01	**0.05**	
VEGA (17)	**−0.03**	**−0.03**	0.02	0.00	**0.08**	**−0.07**	**−0.05**	**0.06**	**−0.06**	0.02	**0.06**	**0.03**	**−0.03**	−0.01	−0.01	**0.71**

This table presents the correlations among regression variables for the main regressions under the Accruals Approach. Numbers that are significant at least at 10% level are displayed in bold format.

approach to measuring big baths that has been employed in prior research.

Taken together, Table 6 provides support for our hypothesis that big baths taken by more deceptive CEOs are associated with larger increase in information asymmetry following the baths, compared with big baths taken by less deceptive CEOs.

5. Additional analyses and robustness tests

In this section, we first provide robustness tests related our primary analyses. In particular, we examine the effects of our matching procedures as well as other research-design choices. Next, we attempt to investigate the "mechanisms" through which investors learn about the big baths. Finally, we explore the effects of investors' prior experience with CEOs' deceptive (or truthful) speech.

5.1. Robustness

We conduct several tests to assess the sensitivity of our inferences to

5.1.2. Alternative outcome variables

To broaden the scope of our analyses, we also consider trading volume, another commonly employed empirical outcome variables in this line of research. As the literature has used different measures of trading volume, we consider both Turnover and Dollar Volume.[21] Table 7 provides the empirical results and shows, consistent with our

[21] Turnover, calculated as the total monthly trading volume divided by shares outstanding, is a widely used information asymmetry measure in research (e.g. Chae, 2005; Haggard et al., 2015; Leuz, 2003; Mohd, 2005). Dollar volume, calculated as monthly mean of log daily dollar trading volume, is used to proxy for the benefit of information collection (Bhushan, 1989), and also to measure (inversely) the liquidity-related trading costs (Utama & Cready, 1997).

Table 6
Panel A: Main regression – accruals approach.

Variables	(1)	(2)	(3)	(4)
	Amihud	Amihud	Spread	Spread
	Three month	Six month	Three month	Six month
TREAT × POST × DECEPTION	0.0957***	0.105***	0.196***	0.191**
	(2.844)	(3.118)	(2.640)	(2.291)
TREAT	0.132***	0.134***	0.311***	0.282***
	(3.004)	(3.246)	(2.832)	(2.722)
POST	0.00431	0.00813	0.0650**	0.0505
	(0.352)	(0.619)	(2.008)	(1.420)
DECEPTION	0.0775*	0.0723*	0.168*	0.149
	(1.713)	(1.780)	(1.674)	(1.534)
TREAT × POST	−0.0311	−0.0570**	−0.120**	−0.104*
	(-1.503)	(-2.251)	(-2.331)	(-1.725)
TREAT × DECEPTION	−0.188***	−0.180***	−0.338**	−0.326**
	(-3.142)	(-3.209)	(-2.367)	(-2.407)
POST × DECEPTION	−0.0605***	−0.0598***	−0.147***	−0.122**
	(-2.744)	(-2.796)	(-3.262)	(-2.448)
SIZE	−0.104***	−0.101***	−0.306***	−0.297***
	(-6.980)	(-7.325)	(-8.655)	(-8.958)
BTM	0.0740***	0.0623***	0.207***	0.188***
	(3.318)	(3.214)	(4.047)	(4.054)
INCOME	0.0617	0.0717	−0.0161	−0.0352
	(0.891)	(1.164)	(-0.0926)	(-0.213)
LEVERAGE	0.0289***	0.0270***	0.0941***	0.0845***
	(3.315)	(3.231)	(4.463)	(3.993)
RETURN_A_LAG	−0.0378*	−0.0358*	−0.104*	−0.115**
	(-1.915)	(-1.961)	(-1.847)	(-2.269)
INSTOWN	−0.149***	−0.131***	−0.499***	−0.465***
	(-3.412)	(-3.010)	(-4.531)	(-4.252)
ANALYST	−0.00984	−0.0116	−0.0458	−0.0473
	(-0.537)	(-0.666)	(-1.019)	(-1.076)
EARNING_SHOCK	−0.00726	−0.00749	−0.0101	−0.0100
	(-0.652)	(-0.725)	(-0.354)	(-0.369)
ROA_CHANGE	0.00321**	0.00289**	0.00738**	0.00732**
	(1.976)	(1.985)	(2.038)	(2.111)
BEAT	−0.0975*	−0.0974*	−0.211	−0.191
	(-1.748)	(-1.942)	(-1.631)	(-1.553)
DELTA	−0.0348	−0.0401	−0.103	−0.120
	(-0.835)	(-1.112)	(-0.950)	(-1.270)
VEGA	−0.102	−0.0940*	−0.211	−0.183
	(-1.562)	(-1.770)	(-1.309)	(-1.405)
DELTA_M	0.0419	0.0930	0.431**	0.395**
	(0.443)	(1.230)	(2.092)	(2.174)
VEGA_M	−0.0994	−0.135*	−0.534***	−0.473***
	(-1.007)	(-1.710)	(-2.646)	(-2.634)
GENKNLREF_PRIOR	−0.0656	−0.0815	−0.132	−0.131
	(-0.243)	(-0.316)	(-0.201)	(-0.203)
POSEMOEXTR_PRIOR	0.0629	0.0734	0.181	0.193
	(0.888)	(1.043)	(1.025)	(1.082)
SHVALUE_PRIOR	0.844	0.788	2.364	2.245
	(0.778)	(0.801)	(0.966)	(0.980)
ANX_PRIOR	−0.137	−0.171	−0.527	−0.522
	(-0.739)	(-1.024)	(-1.316)	(-1.349)
Observations	3048	6096	3048	6096
Adjusted R^2	0.324	0.311	0.425	0.418
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm

This table represents results for the main OLS regressions under the Accruals Approach. Amihud and Spread are dependent variables, with regressing results shown both the three-month and the six-month as pre and post event window length. Explanatory variables include TREAT, POST, DECEPTION, interaction terms of the three variables, triple interaction term of TREAT × POST × DECEPTION. Control variables include SIZE (log of total assets), BTM (book to market ratio), INCOME (income scaled by total assets), RETURN_A_LAG (lag of annual return), LEVERAGE (leverage), SALEGROWTH (sales growth year over year), INSTOWN (institutional ownership), ANALYST (analyst coverage), EARNING_SHOCK (absolute earnings shock), ROA_CHANGE (change in ROA year over year), BEAT (indicator variable of beating analyst consensus forecast), DELTA (CEO compensation delta), VEGA (CEO compensation vega), DELTA_M (indicator variable of whether delta is missing), VEGA_M (indicator variable of whether vega is missing), GENKNLREF_PRIOR (average word frequency of "reference to general knowledge" words in prior conference calls), POSEMOEXTR_PRIOR (average word frequency of "extreme positive emotions" words in prior conference calls), SHVALUE_PRIOR (average word frequency of "shareholder value" words in prior conference calls), and ANX_PRIOR (average word frequency of "anxiety" words in prior conference calls). Industry fixed effects and year fixed effects are included. Standard errors are clustered at firm level. Robust t-statistics in parentheses ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 6
Panel B: Main regression – special items approach.

Variables	(1)	(2)	(3)	(4)
	Amihud	Amihud	Spread	Spread
	Three month	Six month	Three month	Six month
TREAT × POST × DECEPTION	0.0280**	0.0333**	0.0645**	0.0590**
	(2.210)	(2.524)	(2.440)	(2.113)
TREAT	0.0267	0.0265*	0.0206	0.0177
	(1.644)	(1.745)	(0.508)	(0.482)
POST	0.0133*	0.0138*	0.0282*	0.0281*
	(1.687)	(1.807)	(1.755)	(1.861)
DECEPTION	−0.00215	0.00618	−0.0280	−0.00951
	(-0.141)	(0.409)	(-0.625)	(-0.230)
TREAT × POST	−0.0156*	−0.0195**	−0.0323	−0.0196
	(-1.721)	(-2.097)	(-1.607)	(-1.000)
TREAT × DECEPTION	−0.0234	−0.0251	−0.00305	−0.0145
	(-1.046)	(-1.150)	(-0.0521)	(-0.265)
POST × DECEPTION	−0.0136	−0.0194**	−0.0412**	−0.0467**
	(-1.494)	(-2.124)	(-2.180)	(-2.364)
SIZE	−0.0397***	−0.0382***	−0.138***	−0.132***
	(-6.711)	(-6.688)	(-10.76)	(-10.76)
BTM	0.0619**	0.0629**	0.123**	0.132**
	(2.143)	(2.269)	(2.004)	(2.311)
INCOME	0.0598*	0.0626*	0.0102	0.0257
	(1.662)	(1.894)	(0.116)	(0.312)
LEVERAGE	0.0259*	0.0260*	0.109***	0.0933***
	(1.916)	(1.872)	(2.954)	(2.804)
RETURN_A_LAG	−0.0354***	−0.0338***	−0.0739***	−0.0697***
	(-3.877)	(-4.058)	(-2.915)	(-3.265)
INSTOWN	−0.0947***	−0.0920***	−0.347***	−0.342***
	(-3.922)	(-3.888)	(-5.831)	(-6.173)
ANALYST	−0.0173**	−0.0184**	−0.0524**	−0.0509**
	(-2.112)	(-2.236)	(-2.321)	(-2.431)
EARNING_SHOCK	−0.00226	−0.00267	0.0104	0.0148
	(-0.226)	(-0.284)	(0.341)	(0.573)
ROA_CHANGE	0.000435	0.00184	0.00180	0.00422
	(0.215)	(0.886)	(0.425)	(1.012)
BEAT	−0.00418	−0.00446	0.0283	0.0344
	(-0.296)	(-0.350)	(0.776)	(1.065)
DELTA	−0.00891***	−0.00853***	−0.0303***	−0.0285***
	(-3.266)	(-3.035)	(-4.222)	(-3.876)
VEGA	−0.106*	−0.105*	−0.335*	−0.355**
	(-1.681)	(-1.806)	(-1.962)	(-2.254)
DELTA_M	0.0654	0.0408	0.183	0.121
	(1.173)	(0.716)	(1.026)	(0.628)
VEGA_M	−0.0946*	−0.0729	−0.224	−0.168
	(-1.665)	(-1.254)	(-1.241)	(-0.860)
GENKNLREF_PRIOR	−0.124	−0.117	−0.312	−0.276
	(-1.499)	(-1.456)	(-1.504)	(-1.397)
POSEMOEXTR_PRIOR	0.0292	0.0378	0.0513	0.0666
	(0.996)	(1.327)	(0.741)	(1.044)
SHVALUE_PRIOR	−0.668*	−0.637*	−0.848	−0.674
	(-1.789)	(-1.713)	(-0.995)	(-0.768)
ANX_PRIOR	−0.0713	−0.0625	−0.111	−0.0834
	(-0.949)	(-0.896)	(-0.568)	(-0.475)
Observations	5304	10,608	5304	10,608
Adjusted R^2	0.259	0.254	0.434	0.427
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm

This table represents results for the main OLS regressions under the Special Items Approach. Amihud and Spread are dependent variables, with regressing results shown both the three-month and the six-month as pre and post event window length. Explanatory variables include TREAT, POST, DECEPTION, interaction terms of the three variables, triple interaction term of TREAT × POST × DECEPTION. Control variables include SIZE (log of total assets), BTM (book to market ratio), INCOME (income scaled by total assets), RETURN_A_LAG (lag of annual return), LEVERAGE (leverage), SALEGROWTH (sales growth year over year), INSTOWN (institutional ownership), ANALYST (analyst coverage), EARNING_SHOCK (absolute earnings shock), ROA_CHANGE (change in ROA year over year), BEAT (indicator variable of beating analyst consensus forecast), DELTA (CEO compensation delta), VEGA (CEO compensation vega), DELTA_M (indicator variable of whether delta is missing), VEGA_M (indicator variable of whether vega is missing), GENKNLREF_PRIOR (average word frequency of "reference to general knowledge" words in prior conference calls), POSEMOEXTR_PRIOR (average word frequency of "extreme positive emotions" words in prior conference calls), SHVALUE_PRIOR (average word frequency of "shareholder value" words in prior conference calls), and ANX_PRIOR (average word frequency of "anxiety" words in prior conference calls). Industry fixed effects and year fixed effects are included. Standard errors are clustered at firm level. Robust t-statistics in parentheses ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 7
Alternative information asymmetry measures.

Variables	(1)	(2)	(3)	(4)
	Turnover	Turnover	DOL_VOL	DOL_VOL
	three month	Six month	Three month	Six month
TREAT × POST × DECEPTION	−0.154*	−0.183**	−0.375***	−0.424***
	(-1.933)	(-2.177)	(-3.092)	(-3.199)
Observations	3048	6096	3048	6096
Adjusted R^2	0.420	0.423	0.761	0.765
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm

This table represents results for the OLS regressions under the Accruals Approach, using alternative information asymmetry proxies. Turnover and Dollar Volume are dependent variables, with regressing results shown both the three-month and the six-month as pre and post event window. Explanatory variables include TREAT, POST, DECEPTION, interaction terms of the three variables, triple interaction term of TREAT × POST × DECEPTION. Control variables include SIZE (log of total assets), BTM (book to market ratio), INCOME (income scaled by total assets), RETURN_A_LAG (lag of annual return), LEVERAGE (leverage), SALEGROWTH (sales growth year over year), INSTOWN (institutional ownership), ANALYST (analyst coverage), EARNING_SHOCK (absolute earnings shock), ROA_CHANGE (change in ROA year over year), BEAT (indicator variable of beating analyst consensus forecast), DELTA (CEO compensation delta), VEGA (CEO compensation vega), DELTA_M (indicator variable of whether delta is missing), VEGA_M (indicator variable of whether vega is missing), GENKNLREF_PRIOR (average word frequency of "reference to general knowledge" words in prior conference calls), POSEMOEXTR_PRIOR (average word frequency of "extreme positive emotions" words in prior conference calls), SHVALUE_PRIOR (average word frequency of "shareholder value" words in prior conference calls), and ANX_PRIOR (average word frequency of "anxiety" words in prior conference calls). Industry fixed effects and year fixed effects are included. Standard errors are clustered at firm level. Robust t-statistics in parentheses ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

predictions and with the primary tests, negative and statistically significant estimated coefficients on our test variables. Thus, our findings are not restricted to information asymmetry as measured by Amihud illiquidity and bid-ask spreads.

5.1.3. Other robustness tests

First, we repeat the above analyses by generating quartiles for each deception-word category, instead of using the median cutoff. We additionally use the mean rather than the median of deception scores to divide into high- and low-deception groups. Results reveal that inferences are not sensitive to a particular cutoff standard being used to generate the deception score.

Next, although we employ two different approaches to identifying big baths in the paper, given the importance of this empirical proxy and the fact this is not an obvious choice (i.e., prior research uses a plethora of approaches), as a sensitivity analysis we follow the approach in Bens and Johnston (2009).[22] We find that our conclusions are unaltered using this alternative proxy.

Further, recall that the regressions include year fixed effects. For example, these fixed effects control for any particular effect associated with the financial crisis. As an alternative approach, we replace the year fixed effects with a specific control for the financial-crisis period, and inferences are unaffected.

Big baths are likely to happen when there is a CEO turnover. We control for this possibility by including an indicator variable that equals one if there is a CEO turnover during the event window, zero otherwise. CEO turnovers are identified from the Compustat ExecuComp database, which provides time-series data for top executives in the S&P 1500 firms since 1992. Our results remain consistent after controlling for CEO turnover.

Finally, although Larcker and Zakolyukina (2012) provide validity tests for the linguistic approach we follow in this study, we also conduct additional validity tests. That is, we test whether our measure of CEO deception is positively associated with benchmark beating. Using both analysts' forecasts and prior earnings as benchmarks, consistent with our prediction we find that *DECEPTION* loads positively and is highly statistically significant (after controlling for known determinants of benchmark beating).

We conclude that our inferences are robust to these research-design choices and that the empirical evidence suggests that investors are able to process the information in conference calls and the information environment is differentially affected depending on whether CEOs are deemed to be deceptive or not.

5.2. How do investors learn about big baths and detect truthfulness?

It is interesting and important to consider the "mechanisms" through which our primary results ensue. We clearly acknowledge that by using U.S. data we are not able to completely answer this question as data on individual investors and their characteristics are generally not available. However, to potentially shed some light on these important issues we do the following.

First, we have carefully scrutinized the conference-call transcripts in our sample. Specifically, we have read through them and paid attention to whether and how analysts and investors ask questions related to big baths, and also to company executives' responses to these queries. We provide several examples of such exchanges in Appendix E. As the appendix makes clear, both analysts and investors ask questions related to big-bath accounting, and company executives respond to such questions. Thus, we believe that investors are cognizant of the possible effects of big baths and consequently "pay attention" to company actions, including potentially by scrutinizing CEO speech.

Next, we consider that the results should be stronger when the baths are more visible and salient to investors. Accordingly, we partition the sample based on the medians of (1) institutional ownership, (2) analyst coverage, (3) press coverage, and (4) the magnitude of the baths.[23] The results are reported in Table 8. We observe that the effects are much stronger (and in some cases only present) in the subsamples with higher visibility or salience. It is in these cases that management deception is likely to be visible to investors and to matter (especially the magnitude of the baths) more to investors.[24,25] As these tests are indirect we do not

[22] Using the Bens and Johnston (2009) methodology, we define big baths as restructuring charges (item #376) and asset impairments (items #368 and #380) that exceed one percent of beginning total assets.

[23] Data on press coverage are obtained from RavenPack and aggregated within a fiscal year for each firm.

[24] It is possible that technological developments have made it easier to detect deception over time. That is, the technology becomes more familiar and improved over time. In

Table 8
Mechanism tests.

Variables	(1)	(2)	(3)	(4)
	Amihud	Amihud	Amihud	Amihud
	Low	High	Low	High
	Three month	Three month	Six month	Six month
Institutional Ownership				
TREAT × POST × DECEPTION	0.0257	0.174***	0.0538	0.161***
	(0.635)	(3.207)	(1.374)	(3.021)
Observations	1524	1524	3048	3048
Adjusted R^2	0.358	0.400	0.333	0.390
Analyst Coverage				
TREAT × POST × DECEPTION	0.0554	0.144***	0.0777*	0.142***
	(1.347)	(2.788)	(1.917)	(2.748)
Observations	1524	1524	3048	3048
Adjusted R^2	0.368	0.410	0.351	0.385
Press Coverage				
TREAT × POST × DECEPTION	0.00171	0.212***	0.0114	0.224***
	(0.0368)	(4.315)	(0.267)	(4.427)
Observations	1524	1524	3048	3048
Adjusted R^2	0.321	0.425	0.304	0.417
Bath Magnitude				
TREAT × POST × DECEPTION	0.0642	0.128**	0.0830**	0.121**
	(1.604)	(2.099)	(2.214)	(2.008)
Observations	1524	1524	3048	3048
Adjusted R^2	0.265	0.434	0.243	0.426
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm

This table represents a summary of the cross-sectional test results, with institutional ownership, analyst coverage, press coverage, and bath magnitude as partition variables. Amihud is the dependent variable, with both three-month and six-month as event windows. Treatment baths are identified following the Accruals Approach. Control variables, industry fixed effects, and year fixed effects are included. Standard errors are clustered at firm level. Robust t-statistics in parentheses ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

want to draw strong conclusions from them; however the findings are consistent with the idea that salience matters in investors paying attention to and detecting managerial deception.

Third, we explore which segment of the conference call, prepared remarks versus the question and answer section (Q&A), provides linguistic patterns that are more indicative of management deception and more relevant in driving the upsurge of information asymmetry. Prior literature shows that both segments convey incremental information over the accompanying press release, but that the Q&A section is relatively more informative (Matsumoto, Pronk, and Roelofsen 2011). We calculate deception scores based on the linguistic characteristics from prepared remarks and Q&A individually, and run regressions with *AMIHUD* as the dependent variable for prepared marks deception and Q&A deception separately. As shown in Table 9, management deception indicated by linguistic features in Q&A leads to a more significant decrease in information asymmetry.

5.3. *The effect of previous versus event-window specific management deception*

It is possible that the capital market can form an expectation on the truthfulness or deceptiveness of a CEO based on *prior* earnings-conference calls. For each individual CEO, it could be that the CEO is truthful to investors in general, but deceptive to investors in the event (bath or non-bath) year; or it could be the contrary - the CEO is a deceptive person most of the time, but truthful to investors in the event year. In order to identify whether and how the capital market reacts differently under these two circumstances, we construct a Deception_prior score for each CEO by using the available earnings conference-call transcripts.[26] CEOs with *Deception_prior* score that is above (equal to or below) the sample median of Deception_prior are classified in the high (low) prior deception group, which is indicated by *PRIOR DECEPTIVE* (*PRIOR TRUTHFUL*). We run the regressions for the high and low groups, respectively.

The regression results are presented in Table 10. The main variable

(*footnote continued*)
an untabulated test, we find that the effect is more pronounced in the most recent time period, providing some indirect support for this idea.

[25] In another (untabulated) test, we follow the approach in Haggard et al. (2015) and partition the baths based on how "forced" they are. Specifically, we use the Barton and Simko methodology that relies on the opening Net Operating Assets to identify "forces" and "voluntary" baths. We find that the information asymmetry is higher when the baths are taken by deceptive managers and when the baths are most discretionary (which is consistent with the findings of Haggard et al., 2015).

[26] Specifically, for each CEO, we calculate the average word frequency for the four deception-related word categories – GenKnlRef, PosEmoExtr, Anxiety, and ShareValue – across all available prior quarterly earnings-conference calls. By taking the average of word frequencies, we intend to capture the CEO deception on a general level prior to the bath event, to be compared with the level of CEO deception at the event time. Deception_prior score is generated the same way as DECEPTION, using the average prior word frequencies.

Table 9
Separation of prepared remarks and Q&A.

Variables	(1)	(2)	(3)	(4)
	amihud	amihud	spread	spread
	pr	q&a	pr	q&a
	six month	six month	six month	six month
TREAT × POST × DECEPTION_PR	0.0147		0.0755	
	(0.394)		(0.644)	
TREAT × POST × DECEPTION_QA		0.0744**		0.165*
		(2.196)		(1.939)
Observations	6096	6096	6096	6096
Adjusted R^2	0.304	0.310	0.413	0.419
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm

This table represents results using prepared remarks and Q&A section in conference call, separately, to indicate management deception. DECEPTION_PR is an indicator variable if a CEO is identify as deceptive based on linguistic features in prepared remarks; DECEPTION_QA is an indicator variable if a CEO is identify as deceptive based on linguistic features in Q&A. Amihud and Spread are used as dependent variables, with six-month as the event window. Control variables, industry fixed effects, and year fixed effects are included. Standard errors are clustered at firm level. Robust t-statistics in parentheses ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 10
Partition on prior deception level.

Variables	(1)	(2)	(3)	(4)
	Amihud	Amihud	Amihud	Amihud
	Prior truthful	Prior deceptive	Prior truthful	PRIOR deceptive
	Three month	Three month	Six month	Six month
TREAT × POST × DECEPTION	0.143**	0.0489	0.144***	0.0325
	(2.298)	(1.060)	(3.055)	(0.680)
Observations	1524	1524	3048	3048
Adjusted R^2	0.378	0.338	0.365	0.337
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm

This table presents results of tests partition on prior CEO deception level. Prior truthful and prior deceptive are related to prior deception level of a CEO, identified based on the linguistic features in all prior conference calls. Amihud is the dependent variable, with both three-month and six-month as event windows. Control variables, industry fixed effects, and year fixed effects are included. Standard errors are clustered at firm level. Robust t-statistics in parentheses ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

of interest is the coefficient on the interaction term *TREAT × POST × DECEPTION*. Column 1 represents the regression results for the *PRIOR TRUTHFUL* group, with 3 months as the event window. The coefficient on the interaction term is positive and significant at the 5% level, implying that a prior truthful CEO being deceptive when taking a big bath leads to significant increase in information asymmetry post bath, compared with a prior truthful CEO being truthful when taking a big bath. Column 2 contains the results for the *PRIOR DECEPTIVE* group, with 3 months as the event window. The coefficient on the interaction term is not statistically significant. We observe similar results for regressions using six months as the event window as shown in column 3 and 4.

Table 10 suggests that, if a CEO is deceptive in general, the capital market does not react significantly different whether the CEO is being truthful or deceptive when taking a big bath. However, information asymmetry increases significantly for a generally truthful CEO being deceptive when taking a big bath. It is thus conceivable that the capital market can form an expectation of whether a CEO is truthful or deceptive according to prior earnings-conference calls. If a CEO is perceived to be deceptive in general, it is likely that investors will interpret his or her disclosures with caution. In contrast, investors may less likely to rigorously scrutinize the behavior of a generally truthful CEO, as Mercer (2004) points out that management's reputation is a relatively enduring trait.

6. Conclusion

While some studies find that big baths can improve the information environment, others find that they degrade the information environment. To expand upon prior literature, this paper looks at big baths in conjunction with management deception. In particular, we examine whether management deception can decrease the credibility of big baths and alter investors' perceptions. We find that information asymmetry (proxied for using the Amihud illiquidity measure and bid-ask spreads) increases significantly after big baths taken by deceptive CEOs as compared to those taken by less deceptive CEOs. Thus, investors are able to discern which managers are deceptive and react accordingly. We believe our findings add to the big-bath literature as well as the accounting literature in general.

The measurement of management deception in this paper relies on the findings in Larcker and Zakolyukina (2012). By applying textual-analysis methodology to identify managers who are more likely to engage in such action in order to manage earnings, this paper also contributes to the literature by introducing a managerial factor that may help explain the inconsistent findings in prior studies regarding the impact of big baths on information asymmetry. The study further adds to the literature by studying how management ethics, indicated by the linguistic patterns during conference calls can affect the information environment. Future research can consider alternative textual-analysis techniques such as naïve Bayes and Support Vector Machines to test the validity of our findings and potentially improve the precision in capturing management deception. Finally, we encourage future research to explore the mechanisms behind the findings in this study in more detail, possibly using surveys or interview-based approaches, and possibly also using other institutional settings (e.g., in countries where data on individual investors and their characteristics are available).

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Appendix A. How we compute big baths

(1) Accruals approach

We use two standards in recognizing whether a firm is taking a big bath: (1) if the firm has extreme negative discretionary accruals, estimated from the approach proposed in Kothari, Leone, and Wasley; (2) the firm's incentive of taking a big bath is discernible. Specifically, this standard is applied to distinguish whether an earnings bath is happening when the current-year financial performance is relatively poor compared to its industry peers, i.e. big bath incentive, or when the company achieves superior financial performance and thus inclines to smooth earnings into the future, i.e. earnings smooth incentives. Bens and Johnston (2009) discuss the two different managerial incentives behind large accounting write-offs in their study of restructuring charges and earnings management.

Kothari et al. suggest that the ROA (return on assets) matched discretionary accrual derived from Jones model is a viable measure for earnings management, and this performance-matched approach performs better than incorporating a performance variable in the discretionary accruals regression. Applying this approach, we first estimate discretionary accruals by running the Jones model (illustrated below) cross-sectionally each year using all firm-year observations in the same two-digit SIC code. We require a minimum observations of ten for each two-digit SIC industry and year combinations.

$$TA_{it} = \beta_0 + \beta_1\,(1/ASSETS_{it\text{-}1}) + \beta_2\,\Delta SALES_{it} + \beta_3\,PPE_{it} + \varepsilon_{it}$$

TA_{it} is total accruals, defined as the difference between income before extraordinary items and operating cash flows, scaled by lag of total assets. $ASSETS_{it\text{-}1}$ represents lagged total assets. $\Delta SALES_{it}$ is change in sales scaled by lagged total assets. PPE_{it} is the net property, plant, and equipment scaled by lagged total assets. All data are obtained from COMPUSTAT.

After obtaining the Jones-model discretionary accrual, we match each firm-year observation with another from the same industry (two-digit SIC code) and year with the closest current year ROA, which is calculated as net income divided by total assets. Kothari et al. demonstrate that matching based on the current year ROA is superior to matching on the prior-year ROA. We calculate our performance-matched discretionary accrual, ACCRUAL, as a firm's Jones-model discretionary accrual minus the matched firm's Jones-model discretionary accrual.

The first standard in defining big baths is whether a firm-year is associated with extreme negative accruals. In achieving this objective, we rank performance matched discretionary accruals into quintile and identify observations satisfying standard one if these observations fall under the bottom quintile rank of discretionary accruals. The second standard in defining big baths is whether a firm is experiencing a financial downturn in the current year, relative to other firms in the same industry. We rank firms' basic income, calculated as income before extraordinary items minus special items, into tercile at industry-year level (industry represented by two-digit SIC code) and standard two is met for observations belong to the bottom tercile of the basic income rank. Indicator variable BATH is defined if a firm-year observation satisfies both of these two standards.

(2) Definition of special items – special items approach

In compustat, special itmes (SPI) are defined as unusual and/or nonrecurring items considered special items by the company, including: (1) Adjustments applicable to prior years; (2) After-tax adjustments to net income for the purchase portion of net income of partly pooled companies; (3) Any significant nonrecurring items; (4) Bad debt expense/Provisions for doubtful accounts/Allowance for losses if non-recurring; (5) Current year's results of discontinued operations and operations to be discontinued; (6) Flood, fire, and other natural disaster losses; (7) Interest on tax settlements; (8) Items specifically called "Restructuring/Reorganization", "Special," or "Non-recurring" regardless of the number of years they are reported; (9) Inventory writedowns when separate line item or called non-recurring; (10) Nonrecurring profit or loss on the sale of assets, investments, and securities; (11) Profit or loss on the repurchase of debentures; (12) Recovery of allowances for losses if original allowance was a special item; (13) Relocation and moving expense; (14) Severance pay when a separate line item; (15) Special allowance for facilities under construction; (16) Transfers from reserves provided for in prior years; (17) Write-downs or write-offs of receivables and intangibles; (18) Year 2000 expenses regardless of the number of years they are reported.

Appendix B. Brief summary of the linguistic approach in Larcker and Zakolyukina (2012) [27]

Larcker and Zakolyukina (2012) conduct linguistic analysis on quarterly earnings-conference calls during the period of September 2003 to May 2007, and calculate word frequencies for all the word categories that have been shown by previous psychological and linguistic research to be related to deception. Larcker and Zakolyukina (2012) further regress financial deception indicators on these word frequencies using logit regression and find that deceptive CEOs use significantly more references to general knowledge words, more extreme positive emotion words, fewer references to shareholder value words, and fewer anxiety words.

Each conference call is labeled as "truthful" or "deceptive" if it is associated with a restatement: contains a disclosure of a material weakness, an auditor change, a late filing, or a Form 8-K filing; relates to an irregularity as described in Hennes, Leone, and Miller; involves accounting issues that elicit a significant negative market reaction such as those described in Palmrose, Richardson, and Scholz; involves a formal SEC investigation that leads to an issuance of an Accounting and Auditing Enforcement Release (AAER).

Word categories related to deception are selected based on Vrij (2008), which provides the theoretical framework of explaining an individual's nonverbal behavior during deception, including emotions, cognitive effort, attempted control, and lack of embracement. To construct deception

[27] Please see Appendix D for definitions of deceptive words.

related word categories, Larcker and Zakolyukina (2012) use LIWC, with some word categories expanded by adding synonyms from a lexical database of English WordNet. Larcker and Zakolyukina (2012) also establish word categories specific to conference call setting, namely, references to general knowledge words, shareholder value words, and value creation words.

Appendix C. Definitions of deceptive words and key variables

Category	Abbreviation	Content
Reference to general knowledge	GenKnlRef	you know, you guys know, you folks know, you well know, you long know, you would agree, everybody knows, everybody well knows, everybody long knows, everybody would agree, everyone knows, everyone well knows, everyone long knows, everyone would agree, others know, others well know, others long know, others would agree, they know, they well know, they long know, they would agree, investors know, investors well know, investors long know, investors would agree, shareholders know, shareholders well know, shareholders long know, shareholders would agree, stockholders know, stockholders well know, stockholders long know, stockholders would agree
Extreme positive emotions	PosEmoExtr	amaz*, A-one, astonish*, awe-inspiring, awesome, awful, bang-up, best, bless*, brillian*, by all odds, careful*, challeng*, cherish*, confidence, confident, confidently, convinc*, crack, cracking, dandy, deadly, definite, definitely, delectabl*, delicious*, deligh*, deucedly, devilishly, dynam*, eager*, emphatically, enormous, excel*, excit*, exult, fab, fabulous*, fantastic*, first-rate, flawless*, genuinely, glori*, gorgeous*, grand, grande*, gratef*, great, groovy, hero*, huge, illustrious, immense, in spades, in truth, incredibl*, insanely, inviolable, keen*, luck, lucked, lucki*, lucks, lucky, luscious, madly, magnific*, marvellous, marvelous, neat*, nifty, outstanding, peachy, perfect*, phenomenal, potent, privileg*, rattling, redoubtable, rejoice, scrumptious*, secur*, sincer*, slap-up, smashing, solid, splend*, strong*, substantial, succeed*, success*, super, superb, superior*, suprem*, swell, terrific*, thankf*, tiptop, topnotch, treasur*, tremendous, triumph*, truly, truth*, unassailable, unbelievable, unquestionably, vast, wonderf*, wondrous, wow*, yay, yays, very good
Shareholder value	ShareValue	shareholder value, shareholder welfare, shareholder well-being, value for our shareholders, value for shareholders, stockholder value, stockholder welfare, stockholder well-being, value for our stockholders, value for stockholder, investor value, investor welfare, investor well-being, value for our investors, value for investors
Anxiety	Anxiety	LIWC category "anx": worried, fearful, nervous, etc. Prior research: Bachenko, Fitzpatrick, and Schonwetter, Bond and Lee, Knapp, Hart, and Dennis, Newman et al. (2003), Vrij (2008)

Appendix D. Definitions of deceptive words and key variables (continued)

Variables	Definition
TREAT	Indicator variable - equals one for each treatment bath
POST	Indicator variable - equals one if in the post bath period
DECEPTION	Indicator variable - equals one if a CEO is in the high deception group
AMIHUD	Monthly mean of the daily absolute return divided by dollar volume: $1{,}000{,}000 \times \lvert ret \rvert \div (prc \times vol)$. Log of one plus this ratio is used in the regressions. Daily CRSP data (variables ret, prc, and vol) are used to calculate the ratio
SPREAD	Monthly mean of the daily bid-ask spread, which is calculated as $100 \times (ask - bid)/[(ask + bid)/2]$. Daily closing bid and ask data from CRSP (variables ask and bid) is used, with crossed quotes (negative spreads) excluded
TURNOVER	Monthly total trading volume divided by shares outstanding
DOL_VOL	Monthly average of log dollar trading volume
SIZE	The natural logarithm of total assets
BTM	Book value of equity divided by market value of equity
REVENUE	Revenue scaled by total assets
INCOME	Net income scaled by total assets
LEVERAGE	Book value of debt divided by market value of equity
ANALYST	

	The natural logarithm of 1 plus the number of analysts issuing earnings forecasts for any horizon during the fiscal period. 0 for any period in which no data are available on I/B/E/S
INSTOWN	The percentage of shares held by institutional investors during the fiscal period; 0 for any period in which no data are available in the 13-F filings
SALEGROWTH	The percentage change in sales from the previous year
DELTA	Expected dollar change in CEO wealth for a 1% change in stock sensitivity (Delta) price (using entire portfolio of stocks and options) computed as in Core and Guay. Data of DELTA are obtained from the website of Lalitha Naveen: https://sites.temple.edu/lnaveen/data/. The data span 1992–2014
VEGA	Expected dollar change in CEO wealth for a 1% change in stock return volatility (using entire portfolio of options) computed as in Guay. Data of VEGA are obtained from the website of Lalitha Naveen: https://sites.temple.edu/lnaveen/data/. The data span 1992–2014
DELTA_M	Indicator variable equals one if data on DELTA is missing
VEGA_M	Indicator variable equals one if data on VEGA is missing
EARNING_SHOCK	Absolute value of earnings shock, which is calculated as actual earnings minus analysts' consensus earnings forecast. Data are obtained from I/B/E/S
BEAT	Indicator variable equals one if actual earnings minus consensus analysts' earnings forecast lies in the range of 0–0.01
RETURN_A	Annual cumulative stock return.
TURNOVER_A	Annual stock turnover (total trading volume divided by shares outstanding).
AMIHUD_A	Log of one plus annual mean of daily Amihud ratio.
GENKNLREF_PRIOR	Average word frequency of GenKnlRef for the prior conference calls
POSEMOEXTR_PRIOR	Average word frequency of PosEmoExtr for the prior conference calls
SHVALUE_PRIOR	Average word frequency of ShareValue for the prior conference calls
ANX_PRIOR	Average word frequency of Anxiety for the prior conference calls

Appendix E. Examples of big-bath related discussions in conference calls analyst (or investor) questions followed by company executive responses

Company Name Call Date	Analyst Name Executive Name	Question Answer
Actuant Corp. Dec 18, 2008	Jeff Hammond - KeyBanc Capital Markets	Okay, great. And then can you give us a better sense of this $10 million to $15 million restructuring? How does that flush out by quarter? Does that kind of exacerbate the downside in the second quarter or does that flush out through the year may be just a little more?
	Andy Lampereur	Yes, it is definitely not a big bath, the way you could book restructuring reserves in the old days. I mean this will be coming in over the balance of the year. I would say, it's going to be more in the third and fourth quarter than what you would see in the second, but there will be some in the second. The more facility oriented projects will be back half of the year, and that's where the bigger dollars are.
Owens-Illinois Jul 26, 2012	Philip Ng - Jefferies & Company, Inc., Research Division	Free cash flow has been somewhat depressed the last few years with a bigger reinvestment cycle and restructuring. So when I look out, going forward, you guys kind of alluded to restructuring. Will that be a big headwind again on cash flow going forward?
	Stephen P. Bramlage	… But we will certainly try to avoid what we did in 2010, where we took a significant haircut in the global free cash flow number and kind of took a big bath approach on the restructuring all at once. It will be much more of a moderated, consistent approach.
WellPoint, Inc. Oct 28, 2009	Peter Costa - FTN Equity Capital Markets	The impairment of intangible assets this quarter, presumably that was mostly related to Illinois and Texas and not really related to the PBM, is that accurate concerning if you're talking about a gain for the PBM?
	Wayne S. Deveydt	The vast majority of that was actually related to the PBM and the revenue. The way you look at the calculations is to base it on revenue, not necessarily the operating earnings, the way the GAAP accounting rules work. So it's the membership associated that was being driven over to the PBM has actually gone away. That actually takes the majority of that writeoff.
Anworth Mortgage Asset Corp Mar 12, 2008	John Ibis - Private Investor	Yes, I have two questions; the first is very simple. Do you see any more writedowns or writeoffs as in the example of this last quarter of $15 million …
	Joseph E. McAdams	Sure, I think I'll take them all as you asked questions. The amount that we have written off relative to our investment of Belvedere actually exceeds our economic exposure to Belvedere by the $7 or $8 million that we discussed before, so we do not anticipate any additional writedowns relative to Belvedere.
	John Ibis - Private Investor	But are there any other writedowns coming down the pike that you know of right now?
	Joseph E. McAdams	No, and again, as we mentioned if anything there should be a reversal of that $7 to $8 million writedown upon the dissolution of Belvedere.
		And final question, I guess – you guys – Rich, you mentioned some product writeoffs in the quarter. Is there an estimate what that number was, incremental?

DreamWorks Animation SKG Jul 29, 2014	Stan Meyers - Piper Jaffray Companies, Research Division	
	Rich Sullivan	Yes, I don't know if we'd actually disclose that number. It is – it traditionally flows to you cost of good lines having, probably, 1%–2% of margin impact in the quarter. We haven't actually sized that. And as you know, we assess our development slate every quarter. So we take these types of write-offs on our occasion. This quarter just happened to be larger than it was last quarter.
Molycorp Inc. Nov 6, 2014	Stan Manoukian - Independent Credit Research LLC	Got you. And then the last question. I was wondering, you still are burning inventory, writing down a lot of inventory. What is the reason for this? And when do you think it will stop? And does it have anything to do with the chloric-acid plant? Were there inefficiencies in the process related to this, or what is it?
	Michael F. Doolan	Well, first of all, most of the writedown does indeed relate to Mountain Pass. And the biggest chunk of it, as you see in our release, our cost per kilogram was $33-plus, but the market price is significantly less than that. So we have to write the inventory down to net realizable value, lower of cost to market, which accounts for most of it.
Oxford Industries Inc. Oct 9, 2007	Jeff Klinefelter - Piper Jaffray	For the next fiscal quarter then we're not anticipating any sort of an inventory writedown or a margin hit, given that sales have improved?
	Doug Wood	No. In fact if anything, none of us like to see this type of economic situation that we have right now, but this is nothing new to us. We have had to manage through this type of situation before. Really, this is when you tighten down your inventories and really make sure you're not too aggressive on your sales projections and don't get too far out there ahead of yourself. So I don't expect anything like that.
Nordstrom, Inc. May 14, 2009	Charles Grom - J.P. Morgan	If I recall Mike on your fourth quarter call, you didn't anticipate an increase to your bad debt preserves, and you guys took about $41 million here in the first quarter. Looking at your guidance, it doesn't suggest that you're going to take anymore reserves over the balance of the year, so I'm just wondering if you could flush it out where you're getting comfortable on that for us.
	Michael G. Koppel	The overall bad debt expense was up $41 million. The actual increase in the reserve for the quarter was about 23–24. Back in the fourth quarter, Charles, our point of view was that we thought unemployment was somewhere in the 9 plus range and that the look of that curve was not going to be as long in terms of the expected length of the unemployment, but I think more recent data over the last several months and then increase in our delinquency rates, certainly it changed our thinking. What we're currently basing our reserves on is an unemployment factor in the 10%–10.5% range which is a big driver of our writeoffs and an expectation that really is not going to flatten out till sometime in the beginning of next year, so with those two changes in point of view, and information that we were seeing out there, it just felt appropriate and prudent to make those adjustments in this first quarter.

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