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DECEPTION IN FINANCIALLY CORRUPT ORGANIZATIONS

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ABSTRACT

Implications of prior field research on verbal cues to deception in financial reports are at odds with findings of laboratory studies on verbal deception cues. Previous laboratory research has identified psychological mechanisms of deceptive behaviors, but far less is known about how such mechanisms function in deceptive financial reports. The purpose of this study was to extend findings of laboratory research on verbal deception cues to deception in financially corrupt firms. Financial corruption in public firms results in substantial adverse impact on a multitude of organizational stakeholders. We predicted that verbal deception cues would positively relate to deception in financially corrupt firms. We used DICTION 7.0 (a computer-aided text analysis software) to assess verbal cues to deception in shareholder letters. To identify financially corrupt firms, we reviewed *Accounting and Auditing Enforcement Releases* available from the US Securities and Exchange Commission. On average, financial corruption in our sample was repeatedly committed for consecutive 4.4 years by groups of 5.7 perpetrators found guilty of the crime. We used a matched-pairs sample study design of financially corrupt firms and a control group of companies that were compliant. We found evidence that shareholder letters signed by senior leaders of financially corrupt firms contained wording signaling negative emotions, which suggested deception. Additionally, the wording in these shareholder letters signaled that the authors attempted to disguise their deception. Our study extends extant knowledge by confirming predictions of laboratory research on verbal deception cues in a natural field setting.

Keywords: financial corruption; deception; DICTION; shareholder letters; CATA

INTRODUCTION

Deceptive financial reports of public firms is an area of crucial interest for investors, auditors, media, employees, policy-makers, and regulators of financial markets (Dyck et al., 2010). Deception in financial reports prevails across economies worldwide (Zahra et al., 2005) and results in large damages to organizational stakeholders (Amiram et al., 2018).

Fleming and Zyglidopoulos (2008) determined that deception by a public firm about its financial performance repeated over time was a phenomenon different from deception committed only once. Fleming and Zyglidopoulos reported that a single incidence of deception indicated internal monitoring practices that were effective to detect the initial deception, while repeated, consecutive incidences of deception was corruption supported by a corrupt culture that over time escalated stakeholder damages and spread within an organization. Following the reasoning of Fleming and Zyglidopoulos, we focus on and define *financial corruption* as repeated, consecutive deception in financial reports. We distinguish *deception* (i.e., a deliberate attempt to mislead others; DePaulo et al., 2003) from *error* (i.e., unintentional communication of falsehoods; DePaulo et al., 2003). An example of financial corruption is the criminal behavior of 16 perpetrators who deceived stakeholders in HealthSouth Corporation's financial reports for eight years (Armenakis and Lang, 2014).

An emerging field research has investigated if verbal deception cues could expose deception in financial reports (see Nicolaides et al., 2018). Similar to Pinocchio's nose that grew in length when Pinocchio told a lie, verbal deception cues point out in language that deception occurs, without revealing what is being concealed (DePaulo et al., 2003). In their review of research on deception cues, Nicolaides et al. concluded that findings were at odds across contexts. Nicolaides et al. reported that a meta-analysis of verbal deception cues in laboratory studies showed that liars used verbal cues signaling *negative* emotions (see DePaulo et al., 2003). In contrast, Nicolaides et al. added that field research in the context of financial reports generally found that verbal cues signaling *positive* emotions were associated with deception (e.g., see Larcker and Zakolyukina, 2012), suggesting that findings of laboratory studies did not extend to deception in financial reports. Bloomfield (2012) argued that Larcker and Zakolyukina's research design was inadequate to investigate verbal deception cues. Nicolaides et al. and Bloomfield concluded that further research should extend existing investigations of verbal cues to deception in financial reports.

The purpose of this study was to extend findings of laboratory research on verbal deception cues (DePaulo et al., 2003) to deception in financially corrupt firms. Following Bloomfield's (2012) recommendations, the design of our study included the following three elements. First, to ensure our investigation included only cases of detectable deception, we focused on financial corruption because leaders of financially corrupt firms had a high level of criminal intent to deceive stakeholders (Ashforth and Anand, 2003; Baer, 2008), as well as verbal deception cues had larger effect sizes in studies involving deception about crimes (DePaulo et al., 2003; Hauch et al., 2015). Second, we investigated verbal cues to deception in shareholder letters because these letters reflected the mindset of leaders signing these letters (see Amernic et al., 2010). Finally, we focused on investigating the cluster of verbal deception cues that received the strongest theoretical and empirical support (cf. DePaulo et al., 2003).

Financial corruption in our sample was repeatedly committed for consecutive 4.4 years by groups of 5.7 perpetrators on average. The majority of these perpetrators were senior managers (e.g., CEOs, CFOs, VPs) who authored deceptive shareholder letters. The letters we investigated were prepared during financial corruption and *prior* to accusations by the US Securities and Exchange Commission (SEC).

Our study contributes to research on verbal deception cues by extending findings of laboratory research on verbal deception cues to organizational practice. We offer prescriptions for parties interested in exposing deception by perpetrators in financially corrupt firms using verbal deception cues.

HYPOTHESES

Certain individual behaviors are associated with deception, including (a) experiencing negative emotions (e.g., deceivers experience guilt about engaging in deception and fear of getting caught) and (b) attempting to control behaviors (e.g., deceivers attempt to control their behavior so as to maintain the deception; Ekman, 2009). Based on the results of 1,338 estimates of 158 deception cues, a meta-analysis provided evidence that adult liars systematically used communication cues that signaled negative emotions and attempts to control their behaviors (DePaulo et al., 2003).

There is a large number of deception cues but most have small effect sizes (DePaulo et al., 2003). Studies using computer analyses of verbal deception cues without *a priori* theoretical predictions are futile (Hauch et al., 2015). Examining a cluster of deception cues gives more valuable information about deception than investigating each cue individually (Vrij, 2008). Meta-analytic evidence showed that using a cluster of deception cues resulted in 70% of truths and lies being classified correctly, including forensic settings (Hartwig and Bond, 2014). Thus, we focused on investigating the cluster of verbal deception cues that received the strongest theoretical and empirical support, as well as those that were relevant to financial corruption.

Negative Emotions

Emotions experienced by liars predict behaviors that differentiate liars from truth tellers. People have little choice about whether an emotion is felt; instead, they experience emotions regardless of their intention (Ekman, 2009). Deceivers appear to experience fear, guilt, shame, and anxiety (Zuckerman et al., 1981). Negative emotions are particularly difficult for people to conceal (Ekman, 2009).

Two types of negative emotions are associated with deceit: fear of being caught and guilt about lying (Ekman, 2009). The greater the deceivers' fear of being caught, the clearer fear cues are (e.g., speech errors, indirect speech). A moderate level of fear can result in behavioral cues salient to a skilled lie catcher. Fear of detection is stronger when stakes are high and involve obtaining rewards and avoiding punishment (DePaulo et al., 2003). Thus, senior managers perpetrating financial corruption should produce strong cues of negative emotions in their communications to stakeholders because they have significant financial incentives to deceive (Johnson et al., 2009) and face substantial penalties for their deception (Karpoff et al., 2008).

Another reason why the strength of fear of detection varies is the level of perceived difficulty of deceiving someone (Ekman, 2009). If someone is known as being tough to fool and has a reputation as an expert in detecting lies, the deceiver will have a strong fear of being caught. Investors, the SEC, auditors, employees, media, and industry regulators were shown to identify deceptive financial reports (Dyck et al., 2010). Therefore, we expect senior managers perpetrating financial corruption to experience a strong fear of detection that results in observable verbal cues of negative emotions in their communications to stakeholders.

Likewise, guilt about deception varies in strength (Ekman, 2009). Guilt is a discomforting emotion triggered by committing crimes. Deceivers experience higher levels of guilt and show stronger cues of negative emotions if the deceit is selfish and involves victims who trust liars and derive no benefit from being deceived. Such deception may cause liars to suffer moral qualms and feelings of discomfort (DePaulo et al., 2003). Because the lie should often be repeated to cover the original deceit, liars underestimate how much they may suffer from deception guilt. Such is the case of financial corruption that is a path-dependent crime, and it is difficult to stop once started (Baer, 2008). When guilt about deception becomes strong, it results in severe mental pain, eroding the sufferer's most fundamental feelings of self-worth (Ekman, 2009). One way to relieve such a pain is confession. For instance, Ramalinga Raju, Chair of board of directors and CEO of Satyam Computer Services, was under increasing pressure to conceal his deception, leading to his confession of lying in financial reports for seven years (Craig et al., 2013).

Meta-analytical evidence has demonstrated that cues of negative emotions have larger effect sizes in lies about crimes (DePaulo et al., 2003; Hauch et al., 2015). Specifically, liars express words signaling negative emotions (e.g., anger, anxiety, sadness) more often than truth tellers do. Additionally, liars use more claims signaling aversion toward a person or an opinion, such as negations and claims reflecting negative emotions (Vrij, 2008). Liars use more negation words (e.g., no, never, not) because these words signal a more defensive tone or denial of crimes that co-occur with negative emotions of liars (Hauch et al., 2015). Because verbal cues of negative emotions in written communications has been linked to deception about crimes, we posited the following hypothesis:

> ***Hypothesis 1:*** Verbal cues of negative emotions expressed in shareholder letters will positively relate to the likelihood of financial corruption.

Attempted Control

Deceivers monitor and try to control their words (Ekman, 2009). Attempted control occurs when deceivers deliberately manipulate the content of their narratives. Paradoxically, deceivers' attempts to control their behaviors to hide deception can provoke cues that instead reveal it. Concealment of negative emotions is a difficult task and requires one to struggle (Ekman, 2009). Even if the deception is successful resulting in no leakage of cues of negative emotions indicative of a lie, the struggle of concealing the emotions itself will be detectable as a deception cue. Liars are likely to be unable to control all aspects of their behavior resulting in verbal and nonverbal discrepancies from truth telling (Zuckerman et al., 1981). For instance, when deceivers control their behaviors they may appear planned, rehearsed, and lacking in spontaneity. Additionally, liars provide answers that are convoluted and indirect (Ekman, 2009). Perpetrators committing repeated financial crimes devote considerable efforts to avoid detection and prosecution (Sanchirico, 2006). Therefore, we expect senior managers involved in financial corruption to dedicate substantial energy to detection avoidance activities, which will result in detectable verbal cues.

Deceivers may give statements providing observers with as little deception-catching opportunities as possible (Vrij, 2008). Deceivers can accomplish this objective by using general, non-specific language. Also, deceivers can prepare the stories they are going to tell in advance and can adhere to a scripted, rehearsed story line each time when asked to repeat it (Vrij, 2008). In contrast, truth tellers recall stories from their memories. Because memory is fallible and reporting skills are imperfect even when people are telling the truth, truth tellers may express self-doubts, claim they do not remember things, or spontaneously correct something they already said (DePaulo et al., 2003). Hauch et al. (2015) found that liars expressed words signaling cognitive processes (e.g., cause, know, ought) and inner thoughts (e.g., think, know, consider) less often than truth tellers.

The key difference between truth tellers and liars is that the former make honest claims, and the latter make illegitimate statements (DePaulo et al., 2003). Because people cannot or do not want to embrace false claims to the extent they embrace truthful statements, liars need to make deliberate attempts to manage their behaviors, emotions, and thoughts to appear truthful. Such deliberate attempts to manage impressions (e.g., impressions of credibility) consume mental resources, resulting in greater self-regulatory busyness. In comparison, truth tellers act naturally and effortlessly. Meta-analytical evidence has shown that liars appear less forthcoming (i.e., unwilling to divulge information) and provide fewer details compared to truth tellers (DePaulo et al., 2003). Moreover, when liars have incentives to deceive, their response length is shorter (DePaulo et al., 2003). Also, liars provide shorter statements (measured by the number of words) compared to truth tellers when deception is about crimes (Hauch et al., 2015). Because verbal cues of attempted control behaviors in written communications has been linked to deception about crimes, we posited the following hypothesis:

> ***Hypothesis 2:*** Verbal cues of attempted control expressed in shareholder letters will positively relate to the likelihood of financial corruption.

RESEARCH METHODOLOGY

Sample Selection

We identified firms involved in financial corruption through three selection criteria. First, non-US-based companies were excluded to avoid confounding effects because of differences in financial reporting practices across countries (Bushman and Piotroski, 2006). Second, we only considered financial reporting in violation of Section 13(b)(2)(a), Section 13(b)(2)(b), or Section 13(b)(5) of the 1934 US Securities Exchange Act as potentially deceptive if the SEC or the US Department of Justice (DOJ) also alleged the violation of Section 10(b)-5 of the 1934 US Securities and Exchange Act or Section 17(a) of the 1933 Securities Act (see Table 1; Karpoff et al., 2017). To sue under these regulations, the SEC and the DOJ must establish some form of *scienter* (i.e., intent to deceive, manipulate, or defraud; Buell, 2011) on behalf of the defendants. Finally, to ensure that the sample included only financial corruption, we used only cases that involved firms and senior managers found guilty of repeatedly violating Section 10(b)-5 or Section 17(a) and restated deceptive financial reports for at least two consecutive fiscal years. For example, in the case of financial corruption in Birmingham-based HealthSouth Corporation mentioned earlier, 16 senior managers were found guilty of lying in HealthSouth's financial reports for eight years (Armenakis and Lang, 2014).

Data Collection Procedures

To identify financial corruption, we collected data from the series of Accounting and Auditing Enforcement Releases (AAERs). The SEC issues AAERs that contain rich descriptions of the nature of the offense, effect of violations on firms' financial reports, perpetrators and firms perpetrating financial crimes, and outcomes of court proceedings. Following the reasoning of Karpoff et al. (2017), we used AAERs to identify financial corruption because AAERs allowed to avoid type one error, which involved classifying compliant firms as financially corrupt and increase statistical power of research design because of accurate classification of violations.

We retrieved copies of 751 AAERs from the SEC Website (sec.gov/divisions/enforce/friactions.shtml; see Table 2). The SEC listed the AAERs chronologically based on the progress of investigations. Because some cases have more than one AAER, we collected the releases in two steps. In the first step, we retrieved an AAER from the SEC's list and reviewed it to identify the name of the firm, nature of the offense, and period of the violation.

To ensure our findings are generalizable for periods before and after the enactment of the US Sarbanes-Oxley Act of 2002 (SOX), we implemented our data collection procedures for two periods of AAER issue dates to include cases that occurred before and after July 30, 2002. Although we relied on AAER issue dates to determine periods of financial corruption, the AAER issue date was not an exact indicator. The initial AAER associated with a given instance of violation lagged an average of 1,017 days after the initial public revelation of the violation (e.g., informal inquiries or formal investigations by regulating agencies; Karpoff et al., 2017). Additionally, there was usually a difference of a few years between issue dates for the first and the final AAERs associated with a given case of violation. For instance, the SEC released the first and final AAERs in the case of HealthSouth Corporation on March 20, 2003, and on April 23, 2007, respectively. Thus, we started with the first available AAER issued in 2003 (AAER 1697 released on January 7, 2003) and ended with AAER 1785 issued on May 19, 2003. All AAERs concerned violations that occurred in fiscal years ending before SOX. Next, to identify violations after SOX, we started with the first available AAER issued in 2010 (AAER 3094 released on January 6, 2010) and finished with AAER 3301 issued on June 27, 2011.

Table 1
US Legislation Prohibiting Deception in Financial Reports

Legislation	Section	Content
1934 US Securities Exchange Act	10(b)-5	It shall be unlawful for any person, directly or indirectly, by the use of any means or instrumentality of interstate commerce, or of the mails or of any facility of any national securities exchange, (a) to employ any device, scheme, or artifice to defraud, (b) to make any untrue statement of a material fact or to omit to state a material fact necessary in order to make the statements made, in the light of the circumstances under which they were made, not misleading, or (c) to engage in any act, practice, or course of business which operates or would operate as a fraud or deceit upon any person, in connection with the purchase or sale of any security.
1933 US Securities Act	17(a)	It shall be unlawful for any person in the offer or sale of any securities (including security-based swaps) or any security-based swap agreement by the use of any means or instruments of transportation or communication in interstate commerce or by use of the mails, directly or indirectly(a) to employ any device, scheme, or artifice to defraud, or (b) to obtain money or property by means of any untrue statement of a material fact or any omission to state a material fact necessary in order to make the statements made, in light of the circumstances under which they were made, not misleading; or (c) to engage in any transaction, practice, or course of business which operates or would operate as a fraud or deceit upon the purchaser.
1934 US Securities Exchange Act	13(b)(2)(a)	Every issuer which has a class of securities registered and every issuer which is required to file reports shall make and keep books, records, and accounts, which, in reasonable detail, accurately and fairly reflect the transactions and dispositions of the assets of the issuer.
1934 US Securities Exchange Act	13(b)(2)(b)	Every issuer which has a class of securities registered and every issuer which is required to file reports shall devise and maintain a system of internal accounting controls sufficient to provide reasonable assurances that (a) transactions are executed in accordance with management's general or specific authorization; (b) transactions are recorded as necessary to permit preparation of financial statements in conformity with generally accepted accounting principles or any other criteria applicable to such statements, and to maintain accountability for assets; (c) access to assets is permitted only in accordance with management's general or specific authorization; and (d) the recorded accountability for assets is compared with the existing assets at reasonable intervals and appropriate action is taken with respect to any differences.
1934 US Securities Exchange Act	13(b)(5)	No person shall knowingly circumvent or knowingly fail to implement a system of internal accounting controls or knowingly falsify any book, record, or account described in Section 13(b)(2)(a) and Section 13(b)(2)(b) of the 1934 US Securities Exchange Act.

In the second step of data collection, we searched for additional releases to identify other relevant AAERs referring to a given case of violation identified in the first step of data collection. We employed the SEC Website search engine, using an organization's name and an employee's name as search criteria. Issue dates for 751 AAERs ranged from December 22, 1998 (AAER 1091) to October 23, 2014 (AAER 3591).

Following Karpoff et al.'s (2017) recommendations, our data collection procedure involved systematic and substantial culling of irrelevant violations to identify financially corrupt firms. To avoid confounding effects because of lumping meaningful categories of violations into one group (see Baucus, 1994), we investigated only cases of financial corruption. Specifically, we reviewed 751 AAERs and found 183 distinct cases of financial violations (see Table 2). Among the 183 violations, 138 did not meet our criteria for sample inclusion because of the following reasons: (a) unrelated to financial reporting; (b) *single* incidences of violation or without financial restatement data available; (c) violations because of *error* or with dismissed SEC's charges; or (d) in non-US-based firms. Thus, we identified 45 cases of financial corruption in US firms, which met our selection criteria. We excluded seven US financially corrupt firms because we could not find matched compliant firms, and nine firms because we could not locate shareholder letters. Therefore, our sample of financially corrupt firms amounted to 29.

Table 2
Number of Distinct Cases of Financial Corruption in US Firms

Distinct violations observed in the AAERs	Number
Violations identified in AAERs	183
Less: Violations unrelated to financial reporting (e.g., illegal insider trading)	53
Financial reporting violations	130
Less: Single incidences of violation, without financial restatement data available, or in non-US-based firms	78
Financial reporting violations in US firms repeated for at least two consecutive years	52
Less: Violations because of error or with dismissed SEC's charges	7
Financial corruption in US firms	45
Less: US financially corrupt firms without matched compliant firms	7
US financially corrupt firms that had matched compliant firms	38
Less: Financially corrupt firms without shareholder letters	9
US financially corrupt firms with matched compliant firms and shareholder letters	**29**

Note: 183 cases of violations were reported in 751 AAERs. AAER = Accounting and Auditing Enforcement Releases.

Matched-Pairs Sample Study Design

To control for potential endogeneity, we followed prior research on financial reporting violations (see Gomulya and Mishina, 2017) by using a matched-pairs sample study design of companies involved in financial corruption and a control group of companies that were compliant. The matched-pairs sample study design is appropriate for investigation of infrequent phenomena and functions as a quasi-experiment that (a) strengthens causal inference, (b) maintains good internal validity, and (c) achieves high external validity (see Grant and Wall, 2009).

Following prior research (Gomulya and Mishina, 2017), we used COMPUSTAT's Fundamentals Annual Database (see wrds-web.wharton.upenn.edu) to identify companies matched on (a) the same industry, measured by the four-digit Standard Industrial Classification code, (b) similar organizational size, measured by total assets at the end of the fiscal year before violations, (c) the same financial reporting requirements, limiting our sample to firms incorporated in the US, and (d) the same time period, measured by fiscal year. We ensured that each matched company was itself not the subject of an AAER or otherwise accused of financial violations. To ensure the equivalency of the matched pairs, we examined the two groups in terms of total assets, revenue, and net income, finding no statistically significant difference between the groups on any of these dimensions.

Organizations within their industries may develop and share procedures for avoiding detection of crimes (Daboub et al., 1995). Additionally, industries vary on the level of monitoring by regulatory agencies (Daboub et al., 1995). Organizational size has been shown to be positively associated with SEC scrutiny (Beneish, 1999). Thus, matching companies on industry and organizational size was our attempt to control against classifying financially corrupt firms as compliant because of potential shortcomings of the SEC to identify financial corruption (Snyder and McKnight, 2004). No firms outside the US were considered for matching to avoid confounding effects because of differences in financial reporting practices across countries (Bushman and Piotroski, 2006). Because changes in macroeconomic conditions were shown to relate to CEOs' unethical behaviors in financial reporting (Bianchi and Mohliver, 2016), we matched firms on the same time period. COMPUSTAT's Fundamentals Annual Database did not provide matched compliant companies for seven cases of financial corruption that were not subject to AAER (e.g., HealthSouth Corporation was excluded because many large firms in the health services industry committed financial crimes; cf. Stowell et al., 2018; see Table 2). Thus, we excluded these seven financially corrupt firms from our sample.

Shareholder Letters

Annual reports to shareholders contain shareholder letters. In shareholder letters, corporate leaders express their business visions, strategies, and interpret financial statements. Shareholder letters reflect the mindset of leaders signing these letters (see Amernic et al., 2010). To locate shareholder letters, we used the Mergent Online database (see mergentonline.com).

We could not identify shareholder letters for nine financially corrupt firms during periods of financial corruption. We excluded these nine cases, resulting in our final sample of 29 financially corrupt firms and 29 matched compliant firms. In Table 3, we listed firm names, periods of deceptive annual financial reports, and perpetrator group sizes for the 29 financial corruption cases. In Table 4, we listed names for the 29 matched compliant firms, periods of matched shareholder letters, and counts of matched letters.

Table 3
Financially Corrupt Firms, Periods of Deceptive Annual Financial Reports, and Perpetrator Group Sizes

Case Number	Financially Corrupt Firm	Period of Deceptive Annual Financial Reports	Perpetrator Group Size
1	Sunbeam Corporation	1996-1997	7
2	Xerox Corporation	1997-2000	11
3	Surety Capital Corporation	1996-1998	3
4	Qwest Communications International, Inc.	2000-2001	19
5	Acrodyne Communications, Inc.	1998-1999	3
6	Symbol Technologies, Inc.	1998-2001	12
7	Thomas & Betts Corporation	1998-1999	3
8	American Bank Note Holographics, Inc.	1996-1997	9
9	Peregrine Systems, Inc.	2000-2001	17
10	Reliant Energy, Inc.	1999-2001	2
11	Merge Healthcare, Inc.	2001-2004	2
12	Bally Total Fitness Holding Corporation	2001-2003	2
13	Brocade Communications Systems, Inc.	2000-2004	4
14	HBO & Company	1997-1998	11
15	Monster Worldwide, Inc.	1997-2005	4
16	Trident Microsystems, Inc.	1993-2005	2
17	Dell, Inc.	2002-2006	7
18	Navistar International Corporation	2002-2004	8
19	Fischer Imaging Corporation	2000-2001	6
20	Affiliated Computer Services, Inc.	1995-2005	2
21	Delphi Corporation	2000-2004	11
22	Ulticom, Inc.	1996-2004	4
23	Carter's, Inc.	2004-2008	2
24	Maxim Integrated Products, Inc.	2000-2005	2
25	Beazer Homes USA, Inc.	2000-2006	3
26	Embarcadero Technologies, Inc.	2000-2004	3
27	Thor Industries, Inc.	2003-2006	1
28	Thor Industries, Inc.	1996-1997	1
29	Dollar General Corporation	1998-1999	5

For the final sample of 29 financially corrupt firms and 29 compliant firms, we identified at least one annual report to shareholders containing a shareholder letter that was issued during a period of financial corruption. We obtained 72 annual reports to shareholders containing shareholder letters issued by the 29 financially corrupt firms. Because annual reports to shareholders were issued after 10-K annual financial reports were filed with the SEC, we reviewed all of them for the presence of disclosed information about financial reporting violations. As a result, we identified two annual reports to shareholders, which revealed some information about the presence of financial corruption. Xerox Corporation and Delphi Corporation admitted in their annual reports to shareholders for fiscal years ending in 2000 and 2004, respectively, that they had ongoing accounting problems that resulted in financial restatements. Thus, we excluded these two annual reports to shareholders and kept the remaining 70 annual reports.

Table 4
Matched Compliant Firms, Periods and Counts of Matched Shareholder Letters

Case Number	Compliant Firm	Period of Matched Shareholder Letters	Count of Matched Shareholder Letters
1	Westpoint Stevens, Inc.	1996-1997	2
2	First Data Corporation	1998-1999	2
3	Savannah Bancorp, Inc.	1997-1998	2
4	BellSouth Corporation	2000-2001	2
5	Merrimac Industries , Inc.	1998	1
6	Lexmark International, Inc.	1998-2001	4
7	Hubbell Incorporated	1999	1
8	Browne & Co., Inc.	1997	1
9	Filenet Corporation	2000	1
10	Duquesne Light Holdings, Inc.	1999-2001	3
11	CSP, Inc.	2003	1
12	Isle of Capri Casinos, Inc.	2002-2003	2
13	Auspex Systems, Inc.	2000	1
14	Bergen Brunswing Corporation	1997-1998	2
15	Riverside Group, Inc.	1997-1999	3
16	Innovex, Inc.	1998	1
17	Sun Microsystems, Inc.	2002, 2004-2006	4
18	Paccar, Inc.	2002, 2004	2
19	American Science and Engineering, Inc.	2000	1
20	Acxiom Corporation	1998-2004	7
21	Visteon Corporation	2000-2003	4
22	Rogue Wave Software, Inc.	2000-2001	2
23	Oxford Industries, Inc.	2004, 2006, 2008	3
24	Microchip Technology, Inc.	2000-2002	3
25	Standard Pacific Corporation	2000-2001, 2003-2005	5
26	IdentiPHI, Inc.	2000-2002	3
27	Polaris Industries, Inc.	2003-2006	4
28	Arctic Cat, Inc.	1997	1
29	ShopKo Stores, Inc.	1998-1999	2

We located an additional 70 annual reports to shareholders containing shareholder letters issued by the 29 compliant firms. We matched these 70 annual reports issued by the compliant firms on the time period same as the 70 annual reports issued by the financially corrupt firms. Thus, our sample included 140 shareholder letters issued by 29 matched pairs of firms. Among the 29 matched pairs, the number of letters ranged from one (nine pairs) to seven letters (the matched pair of Affiliated Computer Services, Inc. and Acxiom Corporation; see Table 4).

Among the 70 shareholder letters issued by financially corrupt firms, 49 (70%) were signed by senior leaders (e.g., CEOs, COOs, VPs), who were identified by the SEC and the DOJ as guilty of conspiring to commit and committing the crime. No signees of the remaining 21 (30%) letters were charged with violations. However, other senior managers who did not sign these 21 shareholder letters perpetrated financial corruption (see Table 3).

Content Analysis of Shareholder Letters

We used a computer-aided text analysis (CATA) to capture verbal cues to deception in shareholder letters. CATA provides an opportunity to evaluate subtle distinctions in linguistic styles reliably and uncover the cognitions of the text author. DICTION 7.0 is a CATA software program that is able to analyze narratives and reveal word usage patterns, as well as differences between texts (Hart and Carroll, 2014). The software program uses (a) categories based on linguistics theory to examine the subtle power of word choice and verbal tone (Hart, 1984); (b) elements of artificial intelligence (Short and Palmer, 2008), such as ability to *learn*, i.e., update its database with every processed text; and (c) a statistical weighting procedure for homographs (i.e., words that are spelled the same but have different meanings; Pennebaker et al., 2003).

DICTION 7.0 covers a broad range of linguistic features, relying on 10,000 search words allocated to categories without overlap (Pennebaker et al., 2003). DICTION 7.0 includes 31 dictionaries, which are word lists, and four *calculated variables*, which result from calculations rather than word list matches. Additionally, DICTION 7.0 has five *master variables* that are built by concatenating dictionaries and calculated variables scores. DICTION has been used in a number of organizational studies (see Short and Palmer, 2008).

Measures

Independent variables: Verbal cues of negative emotions. Verbal cues of negative emotions were measured using three DICTION 7.0's unique dictionaries: *Blame*, *Hardship*, and *Denial*. Higher values of the three dictionaries signal negative emotions associated with deception. For instance, Davis et al. (2012) measured verbal cues of negative emotions of managers in earnings press releases, using the three dictionaries to predict firms' future performance. Verbal cues of guilt and fear have not been clearly determined, but they included verbal cues of negative emotions in general (Ekman, 2009). As presented above, liars use negative comments and words that signal negative emotions caused by guilt and fear (Vrij, 2008). Prior research measured verbal cues of negative emotions by the number of negative comments and complaints (DePaulo et al., 2003) and by the number of words that expressed negative emotions (e.g., hate, worthless, enemy; Hauch et al., 2015). Therefore, among 31 available dictionaries, we selected the *Blame* and *Hardship* dictionaries because they reflected a number of concepts associated with negative emotions, including unplanned vicissitudes (e.g., nervous, painful), censurable human behavior (e.g., infidelity, betrayal), and normal human fears (e.g., grief, apprehension).

Blame was represented with terms designating social inappropriateness (e.g., mean, naive, sloppy) and downright evil (e.g., blood-thirsty, repugnant, malicious; Hart and Carroll, 2014). Additionally, adjectives describing unfortunate circumstances (e.g., rash, morbid, embarrassing) or unplanned vicissitudes (e.g., weary, nervous, painful,) were included. The dictionary also included outright denigrations (e.g., illegitimate, offensive, miserly).

The *Hardship* dictionary contained words that referred to concepts, including natural disasters (e.g., earthquake, tornado, pollution), hostile actions (e.g., bankruptcy, enemies, vices), censurable human behavior (e.g., infidelity, despots, betrayal), unsavory political outcomes (e.g., injustice, exploitation, rebellion), normal human fears (e.g., grief, unemployment, apprehension), and incapacities (e.g., error, cop-outs, weakness; Hart and Carroll, 2014).

Additionally, we selected the *Denial* dictionary to measure verbal cues of negations that signaled a defensive tone or denial of wrongdoing, which co-occurred with negative emotions (Vrij, 2008). Hauch et al. (2015) measured negations by words that expressed negations (e.g., no, never, not). *Denial* was a dictionary that consisted of standard negative contractions (e.g., aren't, shouldn't, don't), negative function words (e.g., nor, not, nay), and terms designating null sets (e.g., nothing, nobody, none; Hart and Carroll, 2014).

Independent variables: Verbal cues of attempted control. Verbal cues of attempted control were measured using DICTION 7.0's unique variables of *Complexity*, *Cognition*, and *Total Words Analyzed*. Higher values of *Complexity* and lower values of *Cognition* and *Total Words Analyzed* signal attempted control behaviors associated with deception. *Complexity* was a measure of the average number of characters-per-word in a given text (Hart and Carroll, 2014). *Complexity* was based on Flesch's (1951) assumption that convoluted phrasings made a text's ideas abstract and its implications unclear (Hart and Carroll, 2014). Courtis (2004) used similar measures based on Flesch's study to capture obfuscation (i.e., more complex discourse structures) in corporate reporting. Because liars were shown to provide convoluted and indirect statements more often than truth tellers (Ekman, 2009), we used *Complexity* to capture convoluted phrasings signaling attempted control.

We employed *Cognition* to capture verbal cues signaling cognitive operations involving retrieval and memory processes. Because liars attempt to control their behaviors by adhering to a scripted, rehearsed story line (Vrij, 2008) and expressing less self-doubts compared to truth tellers (DePaulo et al., 2003), they use fewer verbal cues signaling cognitive operations including retrieval and memory processes (Hauch et al., 2015). To capture verbal cues of cognitive operations, prior research used words related to cognitive processes (e.g., cause, know, ought) and words related to a person's insight (e.g., think, know, consider; Hauch et al., 2015). The *Cognition* dictionary contained words referring to cerebral processes, both functional and imaginative, such as modes of discovery (e.g., learn, deliberate, consider, compare) and domains of study (e.g., psychology, logic, economics; Hart and Carroll, 2014). Additionally, the dictionary contained mental challenges (e.g., question, forget, re-examine, paradoxes), institutional learning practices (e.g., graduation, teaching, classrooms), and three forms of intellection, namely, intuitional (e.g., invent, perceive, speculate, interpret), rationalistic (e.g., estimate, examine, and reasonable), and calculative (e.g., diagnose, analyze, fact-finding; Hart and Carroll, 2014).

Liars who control their behaviors are less forthcoming (i.e., unwilling to divulge information) by providing fewer details, shorter responses (DePaulo et al., 2003), and shorter statements (Hauch et al., 2015) than truth tellers. *Total Words Analyzed* was a measure of the number of words in a given text (Hart and Carroll, 2014). We used *Total Words Analyzed* to measure forthcomingness indicative of attempted control behaviors.

Control variable: Number of shareholder letters. Craig et al. (2013) showed that linguistic characteristics of deceptive communications changed over time across shareholder letters issued by the financially corrupt firm, Satyam. Therefore, we statistically controlled for the number of shareholder letters because the number of letters available for the firms in our sample varied (ranging from one to seven letters; see Table 4). *Number of shareholder letters* was measured using the count of shareholder letters available for a given firm.

Dependent variable: Financial corruption. We coded *financial corruption* as 1 = firms that perpetrated financial corruption (see above) and 0 = firms that were compliant.

Analyses

Given our use of a binary dependent variable and continuous independent variables, logistic regression analysis was appropriate for analysis (see Menard, 1995). Because logistic regression assumes independence of observations, we included only one observation per firm to satisfy this assumption. We had 140 shareholder letters issued by 58 firms. To produce one observation per firm, we followed the approach of Johnson et al. (2009) to data aggregation by averaging data for all shareholder letters when firms had multiple letters. In sum, we obtained shareholder letter scores for 29 firms exhibiting financial corruption and 29 matched firms that were compliant (N = 58 firms). Results from logistic models with the number of observations per independent variable (OPIV) of at least five are reliable, especially so if results are statistically significant (Vittinghoff and McCulloch, 2007). OPIV in our full model with all independent variables included was 9.7, exceeding the required threshold of at least five OPIV.

Interpretation of the odds ratio in logistic regression assumes that values of independent variables range for at least one integer. DICTION 7.0 scores may contain fractionated integers or values of less than 1 (Hart and Carroll, 2014). Therefore, to ensure that our interpretation of results was not out of range, we increased values of the five independent variables (*Blame*, *Hardship*, *Denial*, *Complexity*, and *Cognition*) by a factor of 10. Because DICTION 7.0 reports values of *Total Words Analyzed* without fractioned integers, we kept values of this independent variable in the original form.

RESULTS

In Table 5, we provide descriptive statistics and correlations among all study variables. For 58 firms in our sample, total assets was $3.9 billion on average ($SD$ = 8.1). Net income was $208.8 million on average (SD = 559.2). We examined the logistic regression model to ensure (a) no multicollinearity, using variance inflation factors, (b) the correct specification of the model, using the Hosmer-Lemenshow goodness-of-fit test, and (c) a linear relationship between the independent variables and the logit transformation of the dependent variable, using the Box-Tidwell test (see Menard, 1995).

Table 5
Means, Standard Deviations, and Intercorrelations Among Study Variables

Variables	*M*	*SD*	1	2	3	4	5	6	7
Control variable:									
1. Number of shareholder letters	2.41	1.44							
Independent variables:									
2. Blame	.62	1.31	.04						
3. Hardship	1.36	1.18	-.05	.06					
4. Denial	1.39	1.20	-.06	.05	.07				
5. Complexity	5.26	.23	-.10	-.07	-.14	-.39**			
6. Cognition	8.29	3.90	-.14	.00	-.04	.18	.31*		
7. Total Words Analyzed	1,184.07	528.42	.15	.16	-.31*	.06	.30*	.12	
Dependent variable:									
8. Financial corruption	.50	.50	.00	-.12	.22	.30*	-.04	-.13	-.10

Note: N = 58 firms. *Blame*, *Hardship*, and *Denial* measure verbal cues of negative emotions. *Complexity*, *Cognition*, and *Total Words Analyzed* measure verbal cues of attempted control behaviors. *Financial corruption* is coded as 1 = firms that perpetrated financial corruption; 0 = firms that were compliant. Intercorrelations among the variables were computed using the Spearman's rank correlation coefficient. Tests are two-tailed.
*$p < .05$.
**$p < .01$.

Because logistic regression assumes no significant outliers or influential points, Menard (1995) recommended examination of observations that have Studentized residuals greater than 3 in absolute value and exclude these observations if exclusion results in improvement of model parameters. We identified three observations, in which the Studentized residuals exceeded the absolute value of 3. The three excluded outliers were two financially corrupt firms (Merge Healthcare, Inc. and Bally Total Fitness Holding Corporation) and one compliant firm (Sun Microsystems, Inc.). Removing these observations resulted in the increase in a number of the model's parameters. First, chi-square increased from χ^2 (7) = 16.31, $p < .05$ to χ^2 (7) = 30.83, $p < .01$. Second, explained variance increased from 32.7% (Nagelkerke R^2) to 57.2% (Nagelkerke R^2). Nagelkerke R^2 is a modified version of the coefficient of determination (R^2) used for binary response models (Nagelkerke, 1991). Third, the overall predictive accuracy of correct classification of observations into either financial corruption or compliance categories increased from 70.7% (20.7% above the model having only a constant) to 80% (29.1% above the model with only a constant).

In Table 6, we present results of the logistic regression analysis. In Step 1, we entered our control variable (*number of shareholder letters*). The model with the control variable only did not predict *financial corruption* (χ^2 (1) = .10, $p > .05$).

In Step 2, we entered the six independent variables (*Blame*, *Hardship*, *Denial*, *Complexity*, *Cognition*, and *Total Words Analyzed*). The full model (Step 2) shows the effect of the independent variables on the prediction of *financial corruption*, after controlling for differences in *number of shareholder letters* (χ^2 (7) = 30.83, p < .01; Nagelkerke R^2 = .57). In Step 2, the control variable {i.e., *number of shareholder letters* (b = .73, p < .05)} had an effect on the prediction of *financial corruption*.

Hypothesis 1 predicted that verbal cues of negative emotions in shareholder letters will positively relate to the likelihood of financial corruption. *Blame* (b = .05, p < .05), *Hardship* (b = .09, p < .05), and *Denial* (b = .26, p < .01) positively related to the likelihood of *financial corruption* (see Table 6). Accordingly, shareholder letters issued by financially corrupt firms were more likely to have verbal cues of negative emotions than letters issued by compliant firms. The results indicated that while holding other variables constant, a 10-unit increase in *Blame*, *Hardship*, and *Denial* increased the odds of financial corruption by 5%, 9%, and 30%, respectively. Thus, *Hypothesis 1* was supported.

Table 6
Results of Logistic Regression for Financial Corruption

	Step 1			Step 2		
Variables	***B***	***SE***	***exp(b)***	***b***	***SE***	***exp(b)***
Control variable:						
1. Number of shareholder letters	.06	.19	1.06	.73*	.33	2.08
Independent variables:						
2. Blame				.05*	.03	1.05
3. Hardship				.09*	.05	1.09
4. Denial				.26**	.08	1.30
5. Complexity				1.03**	.37	2.81
6. Cognition				-.07**	.02	.93
7. Total Words Analyzed				-.002*	.001	.998

Note: N = 55 firms. Values of five independent variables (*Blame*, *Hardship*, *Denial*, *Complexity*, and *Cognition*) were increased by a factor of 10. Tests are one-tailed for *Blame*, *Hardship*, *Denial*, *Complexity*, *Cognition*, and *Total Words Analyzed*. Exp(b) is the exponentiation of the b coefficient that is an odds ratio.
*p < .05.
**p < .01.

Hypothesis 2 predicted that verbal cues of attempted control in shareholder letters will positively relate to the likelihood of financial corruption. *Complexity* (b =1.03, p < .01) positively related to the likelihood of *financial corruption*, while *Cognition* (b = -.07, p < .01) and *Total Words Analyzed* (b = -.002, p < .05) negatively related to the likelihood of *financial corruption* (see Table 6). Accordingly, shareholder letters issued by financially corrupt firms were more likely to have verbal cues of attempted control than letters issued by compliant firms. Holding the other variables constant, a 10-unit increase in *Complexity* increased the odds of financial corruption by 181%, while a 10-unit increase in *Cognition* decreased the odds of financial corruption by 7%. A one-unit increase in *Total Words Analyzed* decreased the odds of financial corruption by .2%, while holding the other variables constant. Therefore, *Hypothesis 2* was supported, as well.

DISCUSSION

Contributions

Previous laboratory research has identified psychological mechanisms of deceptive behaviors, but far less is known about how such mechanisms function in deceptive financial reports (see Bloomfield, 2012; Nicolaides et al., 2018). Such knowledge is valuable to uncover deception in financially corrupt firms. Only when deception is exposed, actions can be taken to hold criminals to account. This study extends extant research by confirming predictions of laboratory research on verbal deception cues in a natural field setting. Our results showed that verbal cues of negative emotions and attempted control positively related to deception in shareholder letters authored by leaders of financially corrupt firms.

Findings of this study can be directly applied to the problems organizational practitioners face. Our recommendation for investors, the SEC, auditors, employees, media, and industry regulators who have been shown to identify financial violations (Dyck et al., 2010) is to adopt the approach employed in this research to increase effectiveness of their efforts. For parties interested in exposing deception in financially corrupt firms using verbal deception cues, we recommend that they use the following guidelines. First, use CATA software to analyze shareholder letter(s). The approach used in this study is accessible to all stakeholders who have access to DICTION 7.0 and annual reports to shareholders. The DICTION 7.0 software has a user-friendly graphical interface and comes with a detailed help manual at an accessible cost. US-based public companies publish current shareholder letters in annual reports to shareholders on their respective websites. Second, interested parties can use our matched-pairs sample study design by building samples of companies, matching on the country of incorporation, year, industry, and organizational size. Third, use the four unique dictionaries of *Blame*, *Hardship*, *Denial*, and *Cognition*, as well as the calculated variables *Complexity* and *Total Words Analyzed* to assess verbal deception cues. If the analysis of shareholder letters indicates verbal deception cues, respective annual reports to shareholders should be further investigated for the presence of financial corruption.

Boundary Conditions, Limitations, and Future Research

Our study has two potential boundary conditions. First, we investigated deception in US financially corrupt firms that used the English language. Because of distinctions in financial reporting practices, cultures, and languages across nations, our findings may not apply to firms incorporated in other countries. Second, the focus of this study was on investigating deception in financially corrupt firms. It is unclear how the model applies to deception conceptualized in other settings. Suggestions for future research are to identify alternative contexts to investigate potential boundary conditions of the findings in this study.

This study has two limitations. First, because this study is based on a convenience sample, our findings may not generalize to a population of financially corrupt firms. Future research may consider taking a random sample of the data to confirm our findings. Second, we investigated only cases of financial corruption that were exposed and reported by the SEC. Findings of our study may not generalize to financial corruption that fall outside these selection criteria. Future research may address this limitation using alternative selection criteria.

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