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Forensic Accounting

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Abstract

Forensic accounting serves as a regulatory and investment tool that allows interested professionals to predict whether firms are engaged in financial reporting misconduct. Financial reporting misconduct has severe economic and personal consequences. Not only does such misconduct distort the allocation of economic resources, but investors and employees of these firms incur substantial financial and psychological harms. In essence, forensic accounting aims to mitigate these harms by predicting the likelihood a firm has committed financial reporting misconduct—thus allowing for early detection of such misconduct. In this review, I provide an overview of the most popular forensic accounting techniques in the literature and the effectiveness of such techniques. Although traditional forensic models tended to focus on behavioral characteristics of the executives who commit financial misconduct or to take a purely numerical approach based on financial data, more recent models combine big data analysis with psychological intuitions.

1. INTRODUCTION

Forensic accounting can be considered the financial equivalent of crime scene investigation. Using detailed financial information, forensic accountants rely on analytical methodology to detect financial misconduct. Although most academic research in this area focuses on methodology that can be used to identify financial misconduct at publicly traded companies, many of the techniques are generalizable to other settings.[1]

In this review, I aim to provide an overview of why we care about financial misconduct, popular forensic techniques to detect such misconduct, and the effectiveness of such techniques. However, perhaps the first question in a review of forensic accounting is how to define the misconduct we intend to study, as researchers use a variety of terms to refer to financial misconduct.[2] For concision within this review, and unless stated otherwise, I follow Amiram et al. (2018) and use financial reporting misconduct (or financial misconduct) as an umbrella term for all types of related infractions.[3]

2. CONSEQUENCES OF FINANCIAL MISCONDUCT

To provide context for the importance of forensic accounting, I begin by describing the severe consequences of financial misconduct—and thus highlight why we need tools to detect and prevent such misconduct. Obviously financial misconduct causes significant monetary harm. Indeed, Karpoff et al. (2008a) find that firms lose approximately 29% of their equity value when financial misconduct is revealed (although this estimate is on the upper end of the range). However, victims suffer psychological harms as well. Victims of financial misconduct are, on average, more likely to suffer from broken relationships, reputational damage, and mental and physical health problems (Button et al. 2014). The effects can be especially devastating because the victims are disproportionately elderly (DeLiema et al. 2020). The psychological consequences of these effects can reverberate across the community to even those not directly affected (Gurun et al. 2018), presumably because other individuals also lose faith in the system after witnessing the harms on those close to them and, without trust, investors are more hesitant to participate in financial markets (Giannetti & Wang 2016).

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[1]The practice of forensic accounting is broader than the research would suggest. Although the academic work is focused largely on the investigative feature of forensic accounting (and primarily the use of forensic accounting to detect financial reporting misconduct at public companies, for which data are easily available), the practice of forensic accounting also includes litigation support. Litigation support includes varied topics such as business valuation, divorce valuation, identification of lost and/or future earnings, embezzlement, and expert witness work. Because these areas receive limited coverage in academic research, I do not cover them here. Instead, I would direct interested readers to work by Nunn et al. (2006).

[2]A nonexclusive list of the terminology used in the literature includes fraud, financial misconduct, financial irregularities, misreporting, misrepresentation, earnings management, and earnings manipulation. One explanation for the variation in language is that literature in this area is interdisciplinary, largely deriving from law, accounting, and finance. Each field has its own terminology. For example, lawyers tend to view fraud as the subset of infractions that have met the court's definition of fraud. By contrast, other professions might consider regulatory actions alleging fraud to represent fraud, even if those allegations are settled without an admission of liability. Another explanation is that discretionary accounting choices lie upon a vast continuum. At one extreme, earnings management refers to massaging financial performance within the limits of generally accepted accounting principles (GAAP) and is not illegal. At the other extreme lies fraud proven in a court of law. Literature spanning this entire this continuum is relevant to forensic accounting.

[3]Amiram et al. (2018) provide a multidisciplinary literature review on financial reporting misconduct. Note that most of the empirical research in this area relies on alleged financial reporting misconduct, such as regulatory enforcement actions, rather than proven financial reporting misconduct.

Although investors are the obvious victims of financial misconduct, there are significant consequences for employees as well. For example, following the fraud at WorldCom, 17,000 workers lost their jobs in a single day (Noguchi 2002). And thousands of Enron employees were left hapless after the company's stock price crashed and the firm entered bankruptcy (Paulsen 2002). Not only did these employees lose their jobs and health care, but many lost most of the funds in their retirement accounts, as they were not allowed to sell the Enron stock in their 401(k) plans (Oppel 2001).

Research shows these are not isolated incidents. By combining US census data with Securities and Exchange Commission (SEC) enforcement actions containing the word "fraud," researchers found that employees of firms accused of fraud are more likely to lose their jobs and, if they do retain their jobs, to experience wage declines. In particular, employee wages during the periods after fraudulent financial reporting are approximately 9% lower than a matched control sample, and the separation rate is higher by 12% during and after fraud periods (Choi & Gipper 2019). Arguably, these employees turn to crime to replace their lost income, as Holzman et al. (2019) find that financially motivated crime increases in the geographic regions where fraud firms are located.

One of the most notable findings of Choi & Gipper (2019) is that the consequences of fraud are not limited to upper-level employees. Although much past literature finds that executives and directors who were responsible for fraud are criminally charged, sued, and/or sanctioned in reputational markets, these studies were limited to high-level employees.[4] By contrast, Choi & Gipper (2019) find that workers in the bottom 90% of the pre-fraud wage distribution experience more negative wage effects than the top 10% of employees. This finding suggests that consequences of fraud diverge from culpability—and demonstrates why policy makers focused on job creation and retention for their constituents should consider fraud prevention in their efforts.

In addition to the individual harms, financial misconduct has broad economic consequences as well. Using a theoretical model, Kedia & Philippon (2009) show that misconduct distorts the allocation of economic resources in the economy, as firms hire and invest excessively during periods of financial misconduct. This pattern is consistent with empirical research. As stated previously, firms shed employees after financial misconduct is revealed (Choi & Gipper 2019). Further, after financial misconduct is exposed, firms also reduce their investment activity (Autore et al. 2015, Yuan & Zhang 2016).[5] Kedia & Philippon (2009) show that this pattern is suboptimal; for example, when the hiring and investment are eventually unwound, employees lose their jobs in unfavorable conditions. Further, the resources consumed during periods of financial misconduct could have been put to better use. Consider, for example, Theranos. The billions of dollars and physical space—not to mention employee talent—could have been devoted to far more productive activity.

In sum, financial misconduct has negative personal and economic consequences. Investors in firms engaging in financial misconduct, who are disproportionately elderly, not only lose their funds but can incur devastating psychological trauma. Employees also suffer—even those employees unconnected to the fraud are more likely to lose their jobs and to suffer wage declines. These consequences reverberate throughout the economy, as companies hire and invest excessively during periods of financial misconduct only to shed those resources later when the financial misconduct is uncovered. This distorts the optimal allocation of resources in society.

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[4]For example, Srinivasan (2005) finds that audit committee members at the helm during restatements are far more likely to depart the firm. Similarly, Desai et al. (2006) find that managers are more likely to depart the firm after a restatement. And Karpoff et al. (2008b) find that 93% of executives identified in SEC and Department of Justice enforcement actions lose their job (some face criminal penalties, including jail time).

[5]Presumably firms reduce investment activity at least in part because the cost of capital increases after financial misconduct is revealed (Chava et al. 2010, 2018; Graham et al. 2008; Hribar & Jenkins 2004; Kravet & Shevlin 2010; Yuan & Zhang 2015).

3. FORENSIC ACCOUNTING IN ACTION

It is because of the devastating consequences of financial misconduct that substantial literature attempts to build models predicting which firms are engaged in financial reporting misconduct. This literature usually proxies for financial reporting misconduct using regulatory enforcement actions, firm restatements, and/or (occasionally) class action lawsuits.[6] Most models follow one of two approaches. One approach focuses on the personal and behavioral characteristics of the individuals who perpetrate financial misconduct. The other approach is numbers based and examines the reported data for abnormalities that are theoretically and empirically predictive of misconduct. Over the last decade, however, researchers have begun to merge these approaches by using big data techniques to identify behavioral responses in company disclosures that indicate unease with the financial reporting.[7]

3.1. Personal and Behavioral Characteristics

Standard economic theory suggests that individuals misbehave if it is rational for them to do so (i.e., the expected benefits outweigh the expected costs, where the expected costs consider the punishment and likelihood of detection) (Becker 1968).[8] However, more recent work has gone beyond the rational incentive effects associated with those who commit financial misconduct and focuses instead on personal and behavioral characteristics. The research has yielded several predictive factors. Men are much more likely to commit misconduct than women (Dreber & Johannesson 2008). And those who commit financial misconduct are often considered "overconfident" or "narcissistic" (Schrand & Zechman 2012)—or even "dishonest" (Loewen et al. 2013).

Literature supports these arguments. Indeed, much work suggests that "overconfident" executives overpromise—and then feel compelled to hide declining financial performance by misreporting (e.g., Dechow et al. 2011, Johnson et al. 2009, Schrand & Zechman 2012). These results could explain why financial reporting misconduct occurs disproportionately at founder firms (e.g., Dechow et al. 1995). For example, one recent study found that founder firms were targeted in over 70% of financial misreporting enforcement actions issued by the SEC and Department of Justice from 1976 to 2013 (Anderson et al. 2018). Other studies have reached similar conclusions, noting that financial reporting misconduct is more likely to occur if the CEO belongs to the founding family (Agrawal & Chadha 2005).

Other work, however, suggests that financial reporting misconduct reflects dispositional rather than situational factors, e.g., stable personality traits (Loewen et al. 2013). Indeed, beginning with Weisburd et al. (1990), much work has found that those who commit financial misconduct are

[6]All of these proxies for financial reporting misconduct are imperfect, and much work considers them to be both overinclusive and underinclusive. For discussions of this issue, see Amiram et al. (2018) and Dechow et al. (2010).

[7]The incentives to commit fraud and the relationship between corporate governance and financial misconduct have been covered extensively in other surveys. I would direct interested readers to work by Amiram et al. (2018). In particular, there is very substantial literature examining the relationship between compensation incentives and financial reporting misconduct (Burns & Kedia 2006, Efendi et al. 2007, Erickson et al. 2006).

[8]Executives may receive tangible benefits from financial misconduct, such as increased compensation or job retention, but may also receive intangible benefits, such as prestige or admiration. Although pure rationality is not a complete explanation for when financial misconduct occurs, prior work supports the view that rational incentives matter. For example, firms located closer to the SEC and in areas with greater past SEC enforcement activity (proxies for the intensity of SEC enforcement) are less likely to restate their financial statements (Kedia & Rajgopal 2011).

repeat offenders, perhaps owing to a preference for greater risk-taking. Further, prior legal or regulatory infractions—even those unrelated to financial misconduct—are correlated with future financial reporting misconduct (Davidson et al. 2015, Dimmock & Gerken 2012). Infidelity, too, appears correlated with financial misconduct. Griffin et al. (2019) show that firms with CEOs or CFOs who were listed on Ashley Madison (the website designed to facilitate extramarital affairs) were twice as likely to be accused of misconduct than those without Ashley Madison connections. Much work has also studied how religious behavior is related to misconduct (e.g., Dyreng et al. 2012, Grullon et al. 2010, McGuire et al. 2012), with some work suggesting that religious adherence is negatively correlated with misconduct.

However, cultural norms appear to play as significant a role in predicting misconduct as individual characteristics (if not a greater role). Financial misconduct varies significantly across US localities, and the frequency of misconduct is correlated with other indicators of "bad" behavior. In particular, research has found that financial reporting misconduct is correlated with political fraud (the frequency of prosecutions against elected and appointed public officials); medical misconduct (monetary transfers from pharmaceutical companies to prescribing physicians); and, of course, infidelity (as measured by the percentage of Ashley Madison subscribers) (Parsons et al. 2018). The propensity to commit misconduct is also affected by coworkers (Dimmock et al. 2018).

3.2. Predicting Misconduct from Financial Data

Another line of forensic accounting literature applies a numbers-based approach that identifies financial misconduct using financial data that are, typically, provided by the firm itself. Some of these techniques focus on statistical abnormalities in the data and are sufficiently generalizable that they can be used to examine data integrity in other settings. Others take an accounting-focused approach that is specific to financial statement analysis.

3.2.1. Statistical abnormalities.

In essence, the literature on statistical abnormalities looks for numerical patterns for which there are limited (or nonexistent) theoretical explanations other than financial misconduct. Some of these abnormalities are described below.

3.2.1.1. Target beating.

Conceptually, this approach tests whether a firm reports fewer small losses and/or more small gains around a particular threshold (i.e., the target) than would be expected. As initially reported by Burgstahler & Dichev (1997), the distribution of firm-level earnings for public companies is not smooth. Instead, there are fewer small losses just below zero—and more small gains just above zero—than would be expected (assuming a normal distribution). To measure firm-level earnings, the authors used the firm's annual net income divided by its market value at the beginning of the year. The original figure from Burgstahler & Dichev (1997) is presented below as **Figure 1**.

The common explanation for this kink at zero in an otherwise smooth distribution is that the deviation is caused by human intervention (i.e., without earnings management, presumably many of the firms with small profits would have instead fallen just below zero). However, other papers have proposed alternate explanations. These papers have suggested that the kink is due not to human intervention in financial reporting but to factors such as asymmetric taxes (Beaver et al. 2007) or to sample bias that arises owing to scaling by market value (and thus, by extension, stock price) (Durtschi & Easton 2005, 2009).[9]

[9]Note that Beaver et al. (2007) correct the original calculation used by Burgstahler & Dichev (1997).

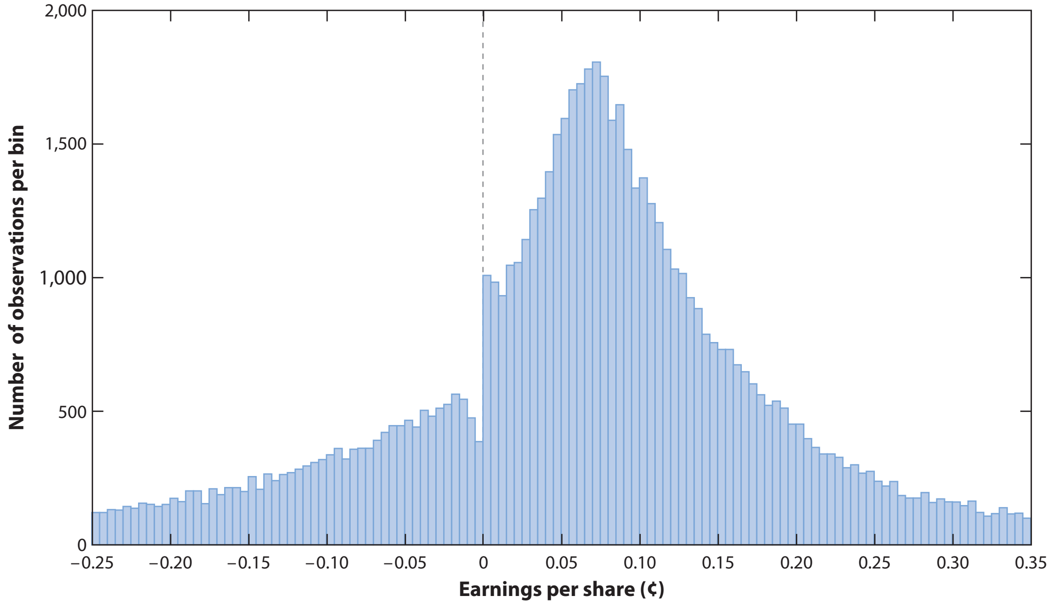

Figure 1

This figure reflects the distribution of earnings (annual net income scaled by market value at the beginning of the year) for all firms in Compustat from 1976 to 1994 with relevant data available. Each bin width is 0.005. Adapted from Burgstahler & Dichev (1997), with permission from Elsevier.

Despite these criticisms, researchers continue to use the intuition from the kink and to apply this intuition in other settings. For example, a similar kink exists in the distribution of analyst forecast errors (defined as a company's reported earnings minus Wall Street's expected earnings) (Degeorge et al. 1999). To my knowledge, there are no studies providing alternate explanations for the kink in this distribution. As such, even if other work is correct that the kink Burgstahler & Dichev (1997) documented in firm earnings is caused by other factors, the intuition that firms may manage earnings or engage in financial reporting misconduct to meet or beat targets appears to hold.

Perhaps prompted by Bernie Madoff—who obsessively focused on meeting targets[10]—more recent work has also used this measure to predict financial misconduct at hedge funds (Bollen & Pool 2009, 2012; Honigsberg 2019a). These studies focus on the monthly returns that hedge funds report to their investors and assume the fund's target is to achieve a return of zero or greater. Researchers assume a target of zero or greater because the number of down months (i.e., loss months) is a significant determinant of fund inflows, even after controlling for total absolute returns (Agarwal et al. 2011). Hedge fund managers are compensated, in part, based on total assets under management, so they have incentives to increase fund inflows, and thus to report monthly returns equal to or greater than zero. The distribution of hedge fund returns, along with the corresponding kink, is below as **Figure 2**.

If anything, the kink in hedge fund returns appears more pronounced than the kink in the distribution of earnings for public companies. One explanation for the larger kink in this setting is that hedge funds may have greater opportunity to manage returns than public companies.

[10]Out of 215 months, Madoff had only 16 months with negative returns (i.e., down months)—making for 92.56% winning months (Bernard & Boyle 2009).

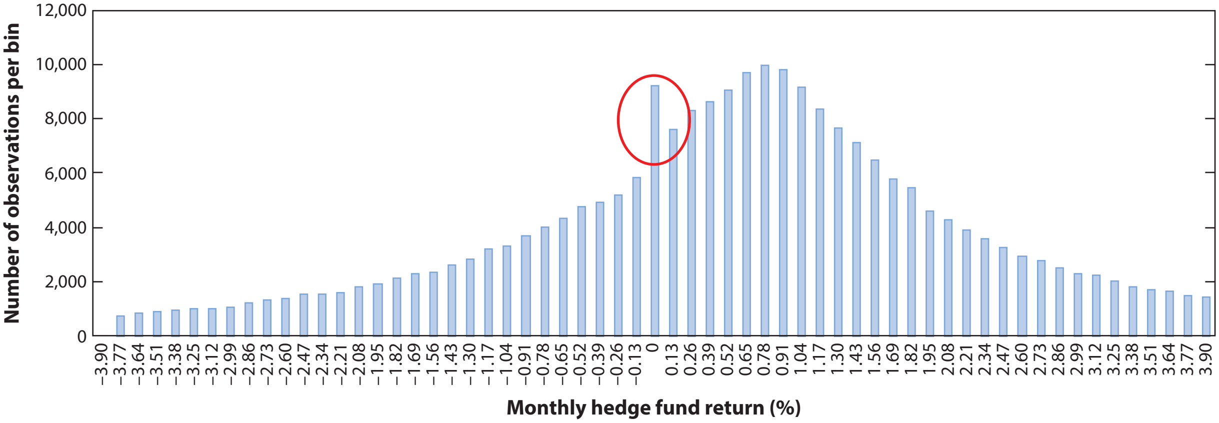

Figure 2

This figure reflects the distribution of monthly hedge fund returns for all funds in the TASS Lipper Hedge Fund Database from 2000 to 2013. The bin width of 13 basis points is set according to the optimal bin width formula provided by Silverman (1986). Adapted from Honigsberg (2019a), with permission from Wiley.

Valuation of hedge fund assets typically involves substantial discretion,[11] many hedge funds are not audited annually, and most hedge funds are subject to minimal regulation (Cassar & Gerakos 2010, Honigsberg 2019a, Restrepo 2019).[12]

3.2.1.2. Benford's law. Another approach used to predict financial misconduct relies on conformance with Benford's law. Benford's law specifies the distribution of the first digit of sufficiently large pools of data. In particular, the law states that, when many underlying distributions are aggregated together, the first digits in the resulting distribution will follow the logarithmic curve below:

$$\mathrm{P}(\mathrm{d}) = \log_{10}(1 + 1/\mathrm{d}), \text{where } \mathrm{d} = 1, 2, \ldots, 9.$$

In other words, the first digit of all observations in a data set is expected to be a "1" 30.1% of the time, a "2" 17.6% of the time, and so on (all other digits will appear with decreasing frequency

[11]Valuation of hedge fund assets is typically considered to involve substantial discretion because hedge funds frequently hold assets for which there is no active market, making it difficult to identify an easily verifiable price. Further, portfolio data are typically not available, so it is generally not possible to identify the specific assets held by the fund. Some funds rely on external monitoring mechanisms (e.g., auditing and third-party pricing) to reduce managerial discretion in valuation, but evidence suggests that these methods are not fully effective (e.g., Brown et al. 2012; Cassar & Gerakos 2010, 2011). Further, many hedge funds do not use these tools—for example, one paper shows that managers have complete discretion to price assets in nearly 20% of funds (Cassar & Gerakos 2011).

[12]At least one set of researchers argues that the observed kink in hedge fund returns is due to hedge fund features such as illiquidity and incentive fees rather than manipulation (Jorion & Schwarz 2014). However, several papers provide additional evidence that the kink is generated by manipulation. Bollen & Pool (2012) identify several suspicious patterns in hedge funds' monthly returns and show that the strongest predictor of detected accounting fraud is the size of the fund's kink at zero. Further, the size of a fund's kink has also been linked to misreporting on 13F filings (quarterly securities filings required for a subset of hedge funds) (Cici et al. 2016), and to pumping up stock prices on the final day of the valuation period (Ben-David et al. 2013). Additional work shows that hedge fund kinks are generally larger in funds for which the manager has greater discretion over valuation (Cassar & Gerakos 2011).

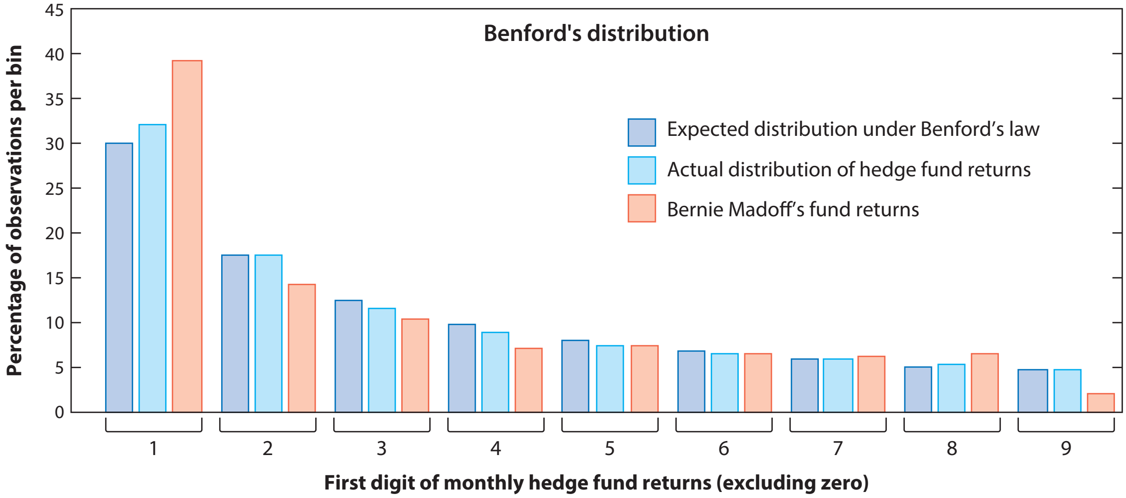

Figure 3

This figure compares three distributions: (*a*) the expected distribution of first digits in a distribution according to Benford's law, (*b*) the distribution of first digits for all hedge funds in the TASS Lipper Hedge Fund database from 2000 to 2013, and (*c*) the distribution of first digits for Bernie Madoff's infamous hedge fund (obtained from Bernard & Boyle 2009).

until "9," which appears as the first digit in only 4.6% of all first digits). Stated broadly, if empirical data are smooth and symmetrical—as is the case for many data sets owing to aspects of the central limit theorem—then those data should conform to Benford's law. However, certain types of errors, such as those introduced through financial reporting misconduct, are likely to result in deviations from the distribution (Amiram et al. 2015).

To illustrate, **Figure 3** presents the distribution of Benford's law, the distribution of all hedge fund returns in the TASS Lipper Hedge Fund Database from 2000 to 2013, and the distribution of Bernie Madoff's returns. As shown, the distribution of all hedge fund returns largely tracks the expected distribution, but Bernie Madoff's returns deviate substantially.[13]

Varian (1972) first suggested that Benford's law could be used to detect errors in reported data. Since then, it has been used to detect systematic rounding of earnings numbers for companies in New Zealand (Carslaw 1988) and the United States (Thomas 1989). Researchers have also shown that conformity to the law can be a useful tool for auditors in detecting errors in tax reporting and internal financial reports (Nigrini 1996, 2012). More recently, Amiram et al. (2015) showed that Benford's law can be used to predict financial misconduct at public companies.

Researchers have used Benford's law to predict misreporting even outside the financial context (Varian 1972). For example, researchers used Benford's law to identify misreporting in ecological data (Cerri 2018), hydrology data (Nigrini & Miller 2007), countries' economic data (Michalski

[13]Using a critical value of 5%, untabulated analysis shows that more than 80% of funds' returns conform to the distribution but that Madoff's returns deviate significantly. To measure deviations at the fund level, I use the Kolmogorov–Smirnov statistic, which relies on the maximum deviation from the expected distribution (for a discussion of measuring conformance to Benford's law, see Morrow 2014, Pike 2008). Under the Kolmogorov–Smirnov statistic, the maximum deviation is determined by calculating the deviation at each point in time (e.g., the deviation from the expected number of 1 values or the deviation from the expected number of 1 and 2 values).

& Stoltz 2013, Nye & Moul 2007), and military expenditures (Rauch et al. 2014). Interestingly, of the 27 countries reporting military data to the United Nations, the United States and United Kingdom had the lowest conformance with Benford's law, indicating the lowest data quality.

3.2.1.3. Abnormalities in post-decimal digits. Similar to research examining trends in the first digit of observations in a distribution, researchers also predict financial reporting misconduct by examining trends in the final digit of observations in a distribution. These studies typically focus on earnings per share—a figure that is typically rounded as appropriate and reported in cents. Earnings per share is calculated by dividing a company's net income by the number of its outstanding shares and is considered one of the, if not the, most important measures of profitability.

To illustrate the effect of rounding, consider that earnings per share of 12.4 cents is reported as 12 cents, whereas earnings per share of 12.5 cents is reported as 13 cents. Therefore, firms are incentivized to report earnings per share numbers with post-decimal digits of five or above, as these digits will be rounded to the higher cent. Following this intuition, academics have found that the numbers above (below) five are under- (over)represented in earnings per share digits beyond the decimal (Craig 1992, Das & Zhang 2003). However, this pattern is reversed for firms with negative earnings (Das & Zhang 2003).

Extending this intuition, Malenko & Grundfest (2014) examine the frequency of the number four beyond the decimal. As illustrated in **Figure 4**, Malenko & Grundfest (2014) find that the number four is underrepresented beyond the decimal point, a pattern they refer to as Quadrophobia.[14] Further, they find that companies with high Quadrophobia scores—where a firm's score is determined based on the incidence of the number four following the decimal over several quarters—are significantly more likely to restate their financial statements, be named as defendants in SEC Accounting and Auditing Enforcement Releases, and be targets in class action securities fraud litigation (Malenko & Grundfest 2014).

3.2.2. Accounting-based predictors. In addition to those papers that predict financial misconduct purely through numerical patterns and/or statistical abnormalities, many forensic accounting papers take a traditionally accounting-driven approach. Using information reported in the financial statements that are publicly disclosed for each public company, these papers apply the authors' knowledge of generally accepted accounting principles and auditing to search for financial reporting misconduct.

3.2.2.1. Abnormal accruals. Much literature attempts to identify poor financial reporting quality by identifying firms with abnormal levels of accruals (e.g., Beneish 1997, 1999; Dechow & Dichev 2002; Dechow et al. 1995; Healy 1985; Jones 1991; Kothari et al. 2005). Under GAAP, a firm's earnings include items that have been earned, even if the cash has not been received. For example, if a firm completes work on a project but has yet to be paid, the firm can accrue the revenue from the project as a receivable that is included in earnings. This is opposed to a cash-based system, which would recognize earnings only when the cash has been received. Theoretically, firms with high abnormal accruals are those most likely to have inflated their performance by accruing

[14]Malenko & Grundfest (2014) assume that, absent human intervention, four will be reported as the first digit following the decimal in 10% of observations. Although the first digit of a distribution follows Benford's law, the distribution of the *n*th digit approaches the uniform distribution (i.e., each digit from 0 to 9 will be represented 10% of the time). Therefore, research frequently assumes that, without human intervention, the final digit of each observation will follow a uniform distribution (Bollen & Pool 2012, Malenko & Grundfest 2014, Straumann 2009).

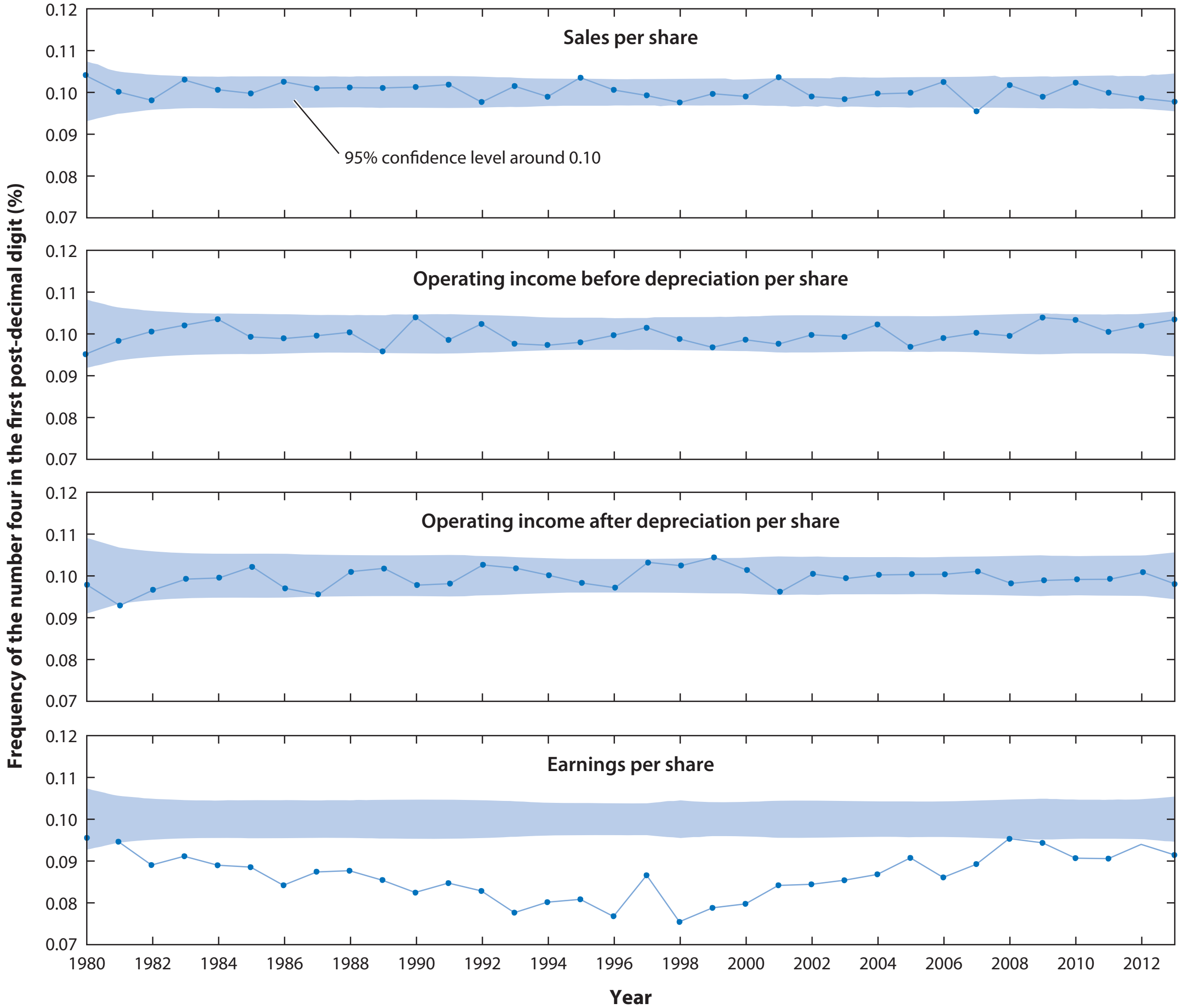

Figure 4

This figure presents a test of the null hypothesis that the frequency of the number four in the first post-decimal digit of various financial ratios is equal to 10% (all ratios are expressed in cents). The figure is based on quarterly data for all firms in Compustat over the 1980–2013 period, for which the corresponding per-share figure is greater than 0.1 cents. Adapted from Malenko & Grundfest (2014), with permission from Joseph Grundfest.

for items that would improve their accounting performance. Empirically, research has found that firms with high abnormal accruals are more likely to be subject to SEC enforcement actions, to restate earnings, and to receive modified audit opinions (Dechow et al. 2010, Francis & Krishnan 1999).[15]

[15]Abnormal accruals are more typically associated with earnings management than with fraud, but I discuss these models here because research has shown that they can predict financial reporting misconduct. There are other measures of earnings management, such as earnings smoothness and asymmetric timeliness (the relative timeliness of loss recognition and profit recognition in earnings), that I do not cover here because I limit myself to the most popular approaches with the greatest predictive value. However, I would direct interested

Most models of abnormal accruals begin by calculating accruals from the financial statements. Thereafter, most approaches estimate expected (or "normal") accruals as a function of accounting variables such as sales growth (or credit sales growth); receivables; and property, plant, and equipment.[16] Using the parameter values from the estimation of normal accruals, the final step in most models is to calculate abnormal accruals as the difference between actual and expected accruals.[17] In essence, methods designed to capture abnormal accruals attempt to identify the process (or mechanism) through which the financial misconduct is perpetrated (e.g., imagine that, to meet a particular earnings target, a firm overaccrues receivables, thus resulting in high abnormal accruals and earnings just above the target).

3.2.2.2. Audit-based predictors. Finally, one growing area of literature uses information on the audit design to predict misreporting. The underlying premise of this work is that there is variation across auditors, and that clients of certain auditors are more likely to engage in financial reporting misconduct. Research in this area began by looking broadly at the accounting firm performing the audit, but it has become more granular over time—from the firm to the firm office to the individual partner.

Stated simply, this work typically finds that auditors can be used to predict financial misconduct. Clients of large audit firms are typically less likely to engage in financial misconduct (Farber 2005, Lennox & Pittman 2010, Palmrose 1988). However, there is variation across the offices of these firms; some offices appear to perform higher-quality work, and their clients are less likely to engage in financial misconduct (Francis et al. 2014). At an even more granular level, this relationship extends to the individual partner leading the audit, as certain partners are likely to be significantly associated with financial reporting misconduct (Gul et al. 2013, Knechel et al. 2015, Wang et al. 2015).

Although much of the research on auditing has, to date, been performed using non-US data, it is likely that US-specific work will increase in the coming years as new disclosures provide additional information (much of the relevant information is already disclosed overseas). In particular, the Public Company Accounting Oversight Board (the primary regulator for accounting firms) recently mandated that accounting firms provide Critical Audit Matters in the audit report, and that they disclose the name of the engagement partner leading the audit and the use of foreign component auditors (legally distinct accounting firms that assist the lead auditor in the audits of non-US jurisdictions) (Honigsberg 2019b). As this type of information on the audit design becomes more widely available, it seems likely to become an additional element in prediction

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readers to the excellent surveys by Dechow et al. (2010) and Amiram et al. (2018). One additional interesting paper covered by prior surveys is that by Brazel et al. (2009), which finds that the difference in growth trends in different parts of the financial statements is greater for firms with financial reporting misconduct (e.g., disparity in growth rates between manufacturing space and revenue).

[16]Although this estimation can be performed at the firm level, it is typically performed at an industry level. Firm-level estimation assumes that the parameter estimates do not vary over time and frequently imposes a selection bias as firms may not survive a sufficiently lengthy period to be included.

[17]Although widely used, these models suffer from arguably significant measurement errors [e.g., see McNichols (2000), among others], leading other researchers to propose various modifications. For example, Kothari et al. (2005) suggest that abnormal accruals should be calculated as the difference between accruals at treatment and control firms, where treatment and control firms are matched based on similar performance. And in perhaps the most popular model in recent years, Dechow & Dichev (2002) develop a model that measures abnormal accruals as the standard deviation of the residual from regressing changes in working capital on past, present, and future operating cash flows. This model is widely used in academic work, but it is difficult to use for estimating current year accruals as future operating cash flows are unknown. This limits its utility for forensic accounting.

models. For example, Downey & Bedard (2019) show that misstatements are generally higher for engagements with greater foreign component auditor participation.

3.3. Merging Behavioral and Quantitative Measures

Although traditional forensic accounting research was siloed and examined either executives' behavioral characteristics or financial reporting data, technological advancements have allowed for a new area of research that combines behavioral intuitions from psychology with big data analysis. For example, psychological research has long suggested that individuals exhibit specific patterns when they engage in deception (e.g., DePaulo et al. 2003, Zuckerman & Driver 1985). Such patterns can include verbal cues (e.g., speech), nonverbal cues (e.g., tone, expressions), and/or physiological responses (e.g., heart rate). Recent work has incorporated these patterns into forensic accounting.[18] Indeed, several relatively recent studies have applied linguistic analysis to corporate texts to detect financial misreporting (see, e.g., Burns et al. 2010; Humpherys et al. 2011; Larcker & Zakolyukina 2012; Loughran & McDonald 2011a,b; Purda & Skillicorn 2015).

Overall, this work suggests that, across different algorithms (e.g., linguistic inquiry and word count software, custom dictionaries, naïve Bayes learning models) and different corporate texts [e.g., the management discussion and analysis section of a company's annual report (MD&A), conference calls], linguistic deception markers have some ability to predict financial reporting misconduct. For example, Hoberg & Lewis (2017) examine text in the MD&A to identify the topics that misconduct firms are more or less likely to include in this section. They find variations in the inclusion of quantitative detail (among other variations) between misconduct and non-misconduct firms that allow them to predict misconduct. And Purda & Skillicorn (2015) use support vector machines to estimate the likelihood of financial misconduct based on the specific words used in the MD&A. They find that this approach performs as well as or better than prior approaches in the literature.

In addition to the written word, oral communications have been shown to predict misconduct. Larcker & Zakolyukina (2012) investigate the conference calls that companies hold with their investors to discuss financial performance and label each call truthful or deceitful based on prior psychological and linguistic research. Deceitful CEOs and CFOs are more likely to discuss general knowledge rather than company-specific information, to present fewer nonextreme positive emotions, to use fewer anxiety words, and to make fewer references to shareholder value. The authors find that identifying financial reporting misconduct using this approach is at least as accurate as models built on financial and accounting variables.

Nonverbal cues, too, have been found to predict financial reporting misconduct. For example, one team of researchers analyzed CEO speech in earnings conference calls for cognitive dissonance using automated vocal emotion analysis software (Hobson et al. 2012). As defined by Hobson et al. (2012, p. 351), "[c]ognitive dissonance is a state of psychological arousal and discomfort occurring when an individual takes actions that contrast with a belief, such as cheating while believing oneself to be honest." Consistent with psychological intuitions, the authors found that their measure of cognitive dissonance is predictive of financial reporting misconduct. Indeed, their model's performance was 11% better than chance and roughly equivalent to models based solely on accounting data.

In sum, forensic accountants have developed a variety of models that predict financial reporting misconduct. Some models take a behavioral approach and examine the characteristics of those

[18]The growth in this area is likely driven by two factors: (*a*) the increasing availability of software programs that allow users to systematically code language and (*b*) an increasingly large supply of machine-readable corporate texts.

who engage in financial misconduct. Other models are based purely on financial data and identify statistical patterns, and/or accounting irregularities, that are theoretically and empirically predictive of misconduct. More recently, researchers have used machine learning and other big data techniques to combine psychological intuitions, such as discomfort with lying, and financial disclosures. These models are still in their infancy but already perform as well as traditional models based purely on financial data.

4. FORENSIC ACCOUNTING AND PREVENTION OF FINANCIAL MISCONDUCT

Many arms of law enforcement routinely rely on forensic accounting to identify misconduct, including techniques noted in this review. The initial regulatory demand for forensic accounting is often attributed to the adoption of the Federal Income Tax, which created a need for the Internal Revenue Service to use forensic accountants to detect tax evasion. Following the lead of the Internal Revenue Service, many other agencies hired forensic accountants, particularly those agencies devoted to investor protection. Forensics can come into play during the inspection and/or enforcement function of these regulators. As an example, in 2018 it was revealed that the Division of Enforcement at the SEC was digging into Quadrophobia (i.e., the case of the missing four in earnings per share) and had reached out to several companies with the conspicuous absence of the number four in their reported earnings (Michaels 2018). The Department of Justice also makes frequent use of forensic accountants, particularly in cases involving white-collar crime. For example, Robert Mueller's key witness in the prosecution of Paul Manafort was a forensic accountant (Layne & Freifeld 2018). In the end, Paul Manafort was convicted on eight charges of bank and tax fraud.

Despite the reliance on forensic accountants, and the substantial resources devoted to the prevention of financial reporting misconduct, it is difficult to quantify the effectiveness of these techniques because we lack a good sense for how frequently financial misconduct occurs. By definition, it is difficult to observe financial misconduct that has not yet been detected, but two notable studies have attempted to do so. First, using the collapse of Arthur Andersen, one study assumes that firms required to switch from Andersen to a new auditor were required to "clean house" by the new auditor (but would have been able to continue any financial misconduct under Andersen, as auditors are hesitant to approve financials one year only to retract that approval later). With this approach, the authors determine that the probability that a firm will engage in financial reporting misconduct in any given year is 14.5% (Dyck et al. 2017). Second, another set of researchers identified a subset of firms that had materially misstated earnings with a high degree of confidence (the researchers used the subset of firms that had backdated stock options to proxy for firms likely to have materially misstated earnings). The study found that, of the firms that the researchers determined had misstated their financial performance with 95% (99%) probability, only 11.5% (16.1%) subsequently restated their financials (Curtis et al. 2018). Jointly, these studies suggest that, in any given year, 10–15% of public companies engage in financial reporting misconduct—and relatively few of these companies disclose that financial reporting misconduct publicly.

5. CONCLUSION

The frequency of alleged financial reporting misconduct, and the lack of disclosure that such misconduct occurred, highlights the need for forensic accounting as a regulatory and investment tool. Financial misconduct has very negative effects, both for the victims of the misconduct (e.g., investors and employees) and for the economy overall. To detect firm misconduct as early as possible, researchers have developed a series of predictive models. Traditionally, the models were rooted in financial data and focused on statistical (or accounting) abnormalities. However, predictive models based on behavioral characteristics have become increasingly popular—and recent models incorporating both psychological and quantitative analysis frequently outperform models built on financial data alone. Going forward, this interdisciplinary approach seems likely to continue, and the growing use of new data analysis techniques, including artificial intelligence and machine learning, seems likely to further improve our ability to predict financial misconduct.

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