HOW PERVASIVE IS CORPORATE FRAUD?

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ABSTRACT

We provide an estimate of the undetected share of corporate fraud. To identify the hidden part of the 'iceberg,' we exploit Arthur Andersen's demise that produced increased scrutiny on AA's former clients and increased the detection likelihood of preexisting frauds. Our evidence suggests that only a third of corporate frauds are detected. We estimate that 11.2% of large publicly-traded U.S. firms on average are engaged in corporate fraud, varying over the business cycle. A bivariate probability model of starting-and-detecting fraud produces similar estimates. We estimate the annual expected cost of fraud to be 1.7% of equity market capitalization.

Starting with Jensen and Meckling (1976), there is a very large literature on the agency costs of public ownership. One of the less emphasized of these costs is fraud. To enrich themselves, managers who own a relatively small fraction of the stock, might be willing to break the law, even when the cost of breaking the law from the company's point of view exceeds its benefits. Is corporate fraud a major component of the agency costs of public ownership? Should regulation do something to reduce this cost?

Before we even try to answer these questions, we need to establish how pervasive corporate fraud is: is the fraud we observe the whole iceberg or just its visible tip? To answer this question we need an estimate of the ratio of the exposed tip to the submerged portion, also known as detection likelihood. Thus far, there have been two approaches in the literature to estimate the submerged portion: Wang (2013), who develops a bivariate probit to identify factors affecting the propensity to commit fraud and the vulnerability of fraud to detection, and Zakolyukina (2018), who uses a structural model of earnings manipulation. In this paper we try a third approach. We exploit the natural experiment created by the 2001 demise of Arthur Andersen (AA), to estimate the fraud detection likelihood.

The simple idea is that after the AA demise, former AA clients were subject to vastly increased scrutiny. They found themselves in the spotlight of the media, investment intermediaries, short-sellers and their internal gatekeepers, and were forced to seek a different auditor. Given the extreme cloud of suspicion that was covering AA clients immediately after the Enron scandal exploded (Chaney and Philipich (2002), Krishnamurthy, Zhou, and Zhou (2006)), the new auditors as well as all other fraud detectors would have strong incentives to clean house in former AA clients. Even if this increased scrutiny might have failed to reveal all the existing fraud, the Kolmogorov axiom of conditional probability allows us to derive an upper bound (and thereby, conservative) estimate of the detection likelihood, which in turn enables us to obtain a lower bound estimate of the pervasiveness of corporate fraud.

The estimated pervasiveness of corporate fraud clearly depends upon the definition of fraud. For this reason, we use several different definitions. The first one is severe financial misrepresentation, where we focus on two measures: i) severe financial reporting violations detected by an auditor identified in Dyck, Morse and Zingales (2010) (hereafter, "DMZ"); ii) severe financial reporting violations identified by the SEC in their Accounting and Auditing Enforcement Releases (AAER) from Dechow et al. (2011). The second notion of fraud we use is intentional misreporting due to misapplication of an accounting rule that leads to financial restatements by Audit Analytics (filtered by the vendor to remove restatements arising from simple mistakes). We call these simply accounting violations.

As a third notion of fraud, we consider the set of misrepresentations and information omissions deemed illegal under *SEC section 10b-5* securities fraud that generate a security class action that is deemed non-frivolous. This notion of fraud is broader than financial misreporting that requires manipulating financial statements. Security class actions also involve 10b-5 cases when firms are sued for failing to reveal material information, with these additional corporate frauds accounting for 35% of observed securities fraud according to DMZ's work.

We find that the detection likelihood ranges from 0.29 (auditor-detected fraud) to 0.52 (AAERs). All of these estimates are statistically significant, and we show they are robust to a host of potential concerns about the representativeness of a sample based on firms audited by Arthur Andersen (e.g. industry focus, regional variation, and importance of IPOs).

Our estimates represent an upper bound of the detection likelihood. The tightness of this bound depends upon how likely it is that the increased scrutiny after AA demise lead to a revelation of all fraud. This assumption is more likely to be true for auditor-detected fraud and accounting violations, because resource constraints in SEC investigations prevent it from pursing all financial misrepresentations and because other non-financial misrepresentation fraud are less likely to be exposed after AA demise. Thus, the most plausible estimates of the detection likelihood come from auditor-detected frauds (0.29) and accounting violations (0.34). By these measures, only a third of corporate frauds are detected. Fraud is indeed like an iceberg with significant undetected fraud beneath the surface.

To test the robustness of our AA experiment approach, we implement the Wang (2013) model. Wang's insight is that the bivariate probit can distinguish between the probability of starting a fraud and the probability of being caught, given that a fraud is started. Our implementation of this alternative method produces a detection likelihood estimate of 0.54, similar to the conservative estimates obtained with the AA natural experiment.

We then move to estimating fraud pervasiveness. The answer depends upon the notion of fraud. We estimate that accounting violations are widespread, with 42.1% of companies committing fraud on average over the business cycle. On the other end of the spectrum, severe financial reporting violations that are sufficiently injurious to warrant an SEC enforcement if detected, are happening in an average of 6.1% of public companies. Our best estimate of fraud pervasiveness is somewhere in between. Using non-frivolous securities violations under SEC rule 10b-5 as a metric for a broad perspective on corporate fraud, we find that 11.2% of all large public corporations are committing fraud.

Having estimated the pervasiveness of fraud, we try to estimate the losses produced by fraud, both the detected and undetected ones. As in Karpoff and Lott (1993), and Karpoff, Lee and Martin (2008) (hereafter, "KLM"), the cost we have in mind is the value lost due to the drop in reputation caused by the fraud. As in Beneish, Lee and Nichols (2013), we allow for the possibility that reputation costs can emerge for not yet detected frauds. Cost estimates from the literature suggest that detected fraud has a cost of 25% of the equity value, while undetected fraud costs 11% of the equity value before the fraud. Based on the proportions of detected and undetected fraud, the average fraud cost is 15.4% of equity value

Putting together our estimates of the pervasiveness of fraud (11.2%) with these estimates of the per-firm cost of fraud (15.4%), we arrive to an expected annual cost of fraud of 1.7% of the total equity value of U.S. public firms. Hence, the annual cost of fraud among US corporations at the end of our sample period is $275 billion. If we compare this fraud cost with the $19.9 billion of SOX compliance cost per year, based on estimates from Hochberg et al. (2009), the benefits of SOX would exceed its costs if SOX were able to reduce the probability that a fraud is initiated by 0.8 percentage points (equal to 8% of the baseline probability).

Our paper builds on a rich literature that measures financial fraud, summarized in Karpoff, Koester, Lee and Martin (2013) (hereafter KKLM). Our focus on undetected fraud is similar to Wang (2013), Winton, Wang, and Yu (2010), and Zakolyukina (2018). In particular, we develop a measure of undetected fraud complementary to Wang (2013) and Zakolyukina (2018). Likewise, our agenda complements the agenda of Dechow, Ge, Larson and Sloan (1996) and Beneish (1999) who provide estimate and a methodology for estimating the likelihood of fraud or misrepresenting accounting through patterns in financial statements. Finally, we build on Karpoff and Lott (1993) and KLM to compute the total cost of this fraud. Our natural experiment of enhanced scrutiny is similar to Fang et al. (2016), who document that an increase in short selling potential increases the probability that a cheating firm is caught.

The rest of the paper proceeds as follows. Section I describes the data and presents summary statistics on caught frauds. Section II explains our methodology. Section III presents the detection likelihood results. Section IV derives the pervasiveness of corporate fraud. Section V provides estimates of the cost of such fraud, and Section VI concludes.

I. Observed Corporate Fraud Measures & Incidence

We start by defining corporate fraud. As KKLM shows, many results on fraud are highly dependent upon the definition of fraud and the database used. To ensure the robustness of our results we rely on three different definitions based on four different data sources. The first definition of fraud is severe financial reporting violations. To identify the severity of the misrepresentation we rely on two different measures. The first measure is financial misrepresentations for which the action of an auditor trigger detection. To construct auditor-detected fraud, we start with SEC rule 10b-5 securities fraud from DMZ's dataset of class actions suits. To make sure the legal class action mechanism captures the frauds, as described in Appendix I, DMZ focus on firms with over $750 million in assets in the pre-audit detection year, with this size cutoff ensuring a large expected payoff to the legal actors. [1] (We maintain this size filter for other fraud measures

[1] The legal industry has set up an automatic process whereby every time a stock price experiences a large drop, specialist attorneys file suits and scour financial reports for misrepresentations. Large, publicly-traded companies offer lucrative possibilities for claims on a suit. For these, it is unlikely that the class action legal structure would miss an opportunity to detect a securities fraud (Coffee, 1986). Note that even if we refer to the class action cases as fraud, from a legal point of view we should refer to them as alleged frauds. Because of the payout structure in directors' and officers' insurance, all class actions either are dismissed or settle. See, for example, the data and discussion in Black, Cheffens and Klausner (2006).

to ensure comparability across samples.) We follow DMZ in imposing filters to ensure that the cases we examine are not frivolous.[2] Finally, to isolate *auditor-detected* financial reporting violations, we restrict to frauds that are revealed either directly by an auditor or indirectly by the triggering action of an auditor – i.e., an auditor issues a qualified opinion and the whistleblower in DMZ is either the company itself or an analyst.[3]

The second measure of severe financial reporting violations is the set of AAERs. Since 1982, the SEC has issued Accounting and Auditing Enforcement Releases (AAERs) during or at the conclusion of an investigation against a company, an auditor, or an officer for alleged accounting and ⁄ or auditing misconduct. We use the AAERs dataset created by Dechow, Ge, Larson and Sloan (2011). The benefit of this sample is that all AAERs are likely to be material violations, as the SEC's statement of an AAER release is considered a severe step meant to attract attention. Yet, the sample may be overly restrictive because the SEC does not have the budget to go after all frauds (e.g. Dechow, Sloan and Sweeney (1996), Miller (2006), and KKLM). Furthermore, as the SEC website notices: "[AAER] only highlights certain actions and is not meant to be a complete and exhaustive compilation of all of the actions that fall into this category."[4] For example, during the period 2001-2014 there were on average 54 AAERs per year versus 220 securities class actions per year (Soltes, forthcoming). We refer to this second measure simply as *AAERs*.

The second definition of fraud is an intentional failure to apply accounting rules. A standard measure of such failures is provided by *accounting restatements.* We use the Audit Analytics database, the most widely employed data on restatements, and focus on intentional failures. Financial restatements are caused by a misapplication of an accounting rule, but misapplication may be unintentional. For example, Hennes et al. (2008) categorize 73.6% of GAO restatements as unintentional misapplications of GAAP

[2]As described in Appendix I, DMZ restrict attention: first, to cases after a 1995 change in the law which forced courts to become more stringent about evidence to certify a case; second, to cases that are not dismissed; and third, to cases without low settlement amounts (below $3 million).
[3] In the latter cases, we re-read the auditor's qualifying opinion and dropped two cases where the fraud could not be plausibly related to the reason why the audit opinion was qualified.
[4] https://www.sec.gov/divisions/enforce/friactions.shtml

accounting. Thus, we use rely on Audit Analytics' filters to separate intentional failures to apply accounting rules from mere clerical errors.

The third definition of corporate fraud is the set of misrepresentations and information omissions deemed illegal under *SEC section 10b-5* securities fraud. Causes of action in 10(b)-5 cases arise from material misstatements or omissions. The omissions category captures a range of misrepresentations that are quite distinct from traditional financial misrepresentations. For example, *"The Department of Justice indicts Sotheby's for price fixing after a long investigation of the art industry. Shareholders sue the firm for failing to disclose that a large portion of their revenues are being derived from the unsustainable high prices achieved through the pricing arrangement with Christie's*." (DMZ Appendix, 2010). In this example, no *financial* reporting violation has occurred, but the omission of mentioning the economic implication of the price fixing is an SEC rule 10b-5 violation. In DMZ, 35% of the 10b-5 violations are omissions of information concerning an underlying legal violation, as in the Sotheby's example. Rather than using the original DMZ set of 10b-5 class actions, we use the updated dataset from the Securities Class Action Clearinghouse, as compiled by Kempf and Spalt (2019). We refer to this measure as *SCAC securities fraud*.

Figure 1 plots the fraction of Compustat large U.S. corporations engaged in detected fraud according to the various definitions. The data are monthly and a company is classified as committing a fraud during a certain month if that months falls in the fraud period determined after detection. When fraud is defined simply as failure to apply accounting rules (Accounting Restatements), the fraction of firms involved in fraud is large (on average 13% per year) and increasing over time (which might reflect the increase complexity of accounting rules). All the other fraud definitions produce a much lower incidence of detected fraud, between 1% and 4% of firms, and a pronounced hump shape centered around the turn of the millennium. This pattern is consistent with Wang, Winton and Yu (2010), who find firms start fraud more in booms because monitoring is lower and managerial reward from cheating is higher.

II. Methodology: Inferring the Detection Likelihood using the Arthur Andersen Experiment

II.1. Experiment Overview

Whereas Figure 1 depicts the incidence of corporate frauds that are eventually caught, our main agenda is to estimate what percentage of all frauds fall into this category, i.e., what percentage of initiated frauds are caught. We refer to this percentage as the detection likelihood.

Our methodology relies on two key ingredients – the Kolmogorov axiom of conditional probability and the Arthur Andersen natural experiment. The pervasiveness of corporate fraud is the probability of a firm engaging in fraud (denoted *F*), regardless of whether it is caught or not: $\Pr(F)$. What we observe instead is the joint event of a firm engaging in fraud and being caught: $\mathbf{Pr}(\boldsymbol{F}, \boldsymbol{caught})$. (We will use the convention of bolding the variables we observe). By the law of conditional probability, the unconditional probability of engaging in a fraud can be written as:

$$\Pr(F) = \frac{\boldsymbol{Pr}(\boldsymbol{F},\boldsymbol{caught})}{Pr(caught|F)}. \tag{1}$$

Thus, if we knew the denominator, $\Pr(caught \mid F)$, we could calculate $\Pr(F)$.

Our main experiment compares the "normal" revelation of corporate fraud with the incidence of fraud in a sample where scrutiny increased substantially to derive an upper bound of $\Pr(caught \mid F)$ and thus a lower bound of $\Pr(F)$. Our natural experiment is similar to Fang et al. (2016), who show that an unexpected increase in a stock's short selling potential increases the probability that a cheating firm is caught. In our experiment, the sample of firms under enhanced scrutiny is the set of Arthur Andersen (AA) clients after the AA demise following the Enron scandal. On October 22, 2001 Enron acknowledged an SEC inquiry concerning possible conflicts of interest in various partnerships (Barton, 2005). On November 23, 2001, the NYT ran an article with the headline: "From Sunbeam to Enron: Andersen's Reputation Suffers". Thus, we assume that the period of enhanced scrutiny started after November 30, 2001, a date to which we refer as the watershed date.[5] Since roughly one fifth of all large publicly traded firms had AA as

[5] As a robustness test, we shifted the beginning of the detection period one month backward or one month forward: the results are substantially unchanged.

their auditor in 2001, this event provides a natural experiment of increased scrutiny of firms. As in Fang et al. (2016), we look at the revelation of fraud started before the watershed date. Thus, we can ignore any deterrence effect, since the enhanced scrutiny produced by the Enron's crisis was unexpected.

The new auditors are one likely source of the increased scrutiny (Chen and Zhou (2007)). Kealy et al. (2007) find that the audit fees charged by AA successors to AA former clients when they switched after Enron are positively related to the length of AA tenure with those clients, suggesting that there is a perceived risk associated with AA clients, which needs to be mitigated with additional monitoring. This enhanced scrutiny is also consistent with Nagy's finding (2005) that smaller ex-AA clients have lower discretionary accruals after switching to a new auditor.

Nevertheless, new auditors are not the only source of enhanced scrutiny. As Chaney and Philipich (2002) and Krishnamurthy, Zhou, and Zhou (2006)) show, after the Enron scandal exploded all AA clients got under a cloud of suspicion. Investment intermediaries and internal gatekeepers of AA clients had stronger incentives to scrutinize their firms thoroughly to clear them of the shadow of suspicion. Likewise, short sellers and the media had special incentives to focus their attention on AA clients in search for the next big scandal.

II.2. Identification Assumption 1: AA firms are not different in 1998-2000

Our first assumption is that in the period before AA's demise (specifically 1998-2000), fraud (F) was equally likely in AA firms and non-AA firms ($\overline{AA}$):[6]

Assumption 1: $$Pr(F \mid \overline{AA}) = Pr(F \mid AA)$$

AA's indictment by the Department of Justice and its initial conviction for obstruction of justice may make this a surprising assumption. Yet, the initial conviction of AA was for obstruction of justice, not for being a bad auditor, and it was unanimously overturned upon appeal.

More convincingly, the accounting literature has concluded that there was no difference between AA and other auditors in terms of auditing rigor. In a matched sample, Agrawal & Chada (2005) find that

[6] To keep notation simple, we do not include time subscripts. We make the timing clear in the text.

the existence of AA as the auditor is not associated with firms having more restatements. Likewise, controlling for client size, region, time and industry, Eisenberg & Macey (2004) find that AA clients did not perform any better or worse than other firms. Nevertheless, we re-test this assumption for assurance and because our sample of large U.S. corporations is different from the aforementioned studies.

Table 1 reports summary statistics, comparing the characteristics and industry of AA clients and non-AA clients during the period 1998-2000. The set of firms are Compustat large (>$750 million in assets) U.S. incorporations. We identify auditors using the Compustat "AU" item, mapping the auditor who signs a financial statement to the calendar month-year of the report. We use two sets of non-AA clients: all non-AA clients and the subset of all non-AA clients that are audited by another of the Big Five audit firms. Statistics are collapsed to one observation per firm over the time period. A firm appears in multiple columns only if it switches auditors. Because of auditor transitions and firms' delisting during the 3-year period, the sample of AA firms is larger than in the subsequent tables, where we require a firm to be audited by AA in 2001.

Panel A reports that AA clients are statistically similar to other Big Five clients in assets, sales, and EBITDA, but have higher leverage (long term debt-to-assets). The leverage difference suggests a difference in industry composition, which is what we present in Panel B. For example, compared to Big 5 auditors that are not AA, AA have at least 2 percentage points less clients in the industries of Banks & Insurance, Retail & Wholesale, and Computers, while having 2 percentage points more clients in the industries of Utilities, Refining & Extractive, Communication & Transport, and Services & Healthcare. We return to these industry compositional differences in our empirical specifications.

Were AA clients more fraudulent? In Table 2, we consider this question using eight measures of fraud, collapsed to one observation per firm for the 1998 – 2000 period before AAs demise (allowing, as before, a firm to have two representations if it switched to/from AA in this period). For the discrete variables of caught fraud – *auditor-caught frauds, AAERs, restatements*, and *SCAC securities fraud*— we define a fraud event if the event ever occurs in the three-year period. Thus, to compare the detected fraud in this table to those in Figure 1 (and to those in the subsequent tables) we need to divide the reported number by three. In addition to these measures of fraud, we include measures of fraud likelihood based on a continuous measure from the accounting literature. We include both the probability of accounting manipulation score (Beneish, 1999) [*ProbM*][7] and the probability of fraud score of Dechow, Ge, Larson and Sloan (DGLS 2011) [*FScore*].[8] Following Beneish (1999) and DGLS (2011), we also consider a discrete version of the *ProbM* and *FScore* in the form of a threshold dummy variable with the authors considering a firm above the threshold as indicating a strong likelihood of being a manipulator.

Panel A of Table 2 reports that for all eight measures of fraud, AA clients are never more likely to be conducting fraud. Based on the measures from the accounting literature, AA clients show lower scores, indicating they are less likely to be committing fraud. These results do not account for the above-mentioned leverage and industry differences.

In Panel B, Table 2 we report estimates from multivariate estimations of fraud likelihood using accounting literature measures of *probM*, the indicator *probM > -2.2*, *FScore*, and the indicator *FScore >1.4* . For each estimation, our variable of interest is an AA dummy, and we include a set of controls for size (log assets, and sales/assets) along with debt (LT Debt/Assets), and profitability (EBITDA/Sales). When we estimate the threshold models (columns 3, 6, 9, and 12), we estimate via logit instead of OLS. All columns include year fixed effects. Columns 2, 3, 5, 6, 8, 9, 11, and 12 include industry fixed effects (where the industries are those of Table 1). Columns 2, 5, 8, and 11 include industry*year fixed effects. (We do not include this further interaction for the logit, as the estimation does not consistently converge uniquely.) In columns 4-6 and 10-12, we restrict the non-AA firms to be Big 5 accounting firm clients only.

Across all specifications, the coefficient on the AA dummy is never positive and significant. In columns 1 and 3, the AA dummy is negative and significant (i.e., AA firms are associated with *less*

[7] Appendix II details the calculations for the ProbM score. ProbM is a score with no natural scale. The mean and standard deviation of ProbM in our sample are -2.325 and 1.357, respectively. According to Beneish (1999), a score greater than -2.22 indicates a strong likelihood of a firm being a manipulator.

[8] We thank Weili Ge for the FScore data. We use their FScore measure from model 2 of the paper, which includes financial statement variables and market data. FScore is a score variable, scaled to imply that a score of 1.00 indicates that the firm has no more probability of AAER fraud than the unconditional probability. In our sample, the mean and standard deviation of Fscore are 1.785 and 10.57, respectively.

probability of manipulation). Being an AA client does not significantly affect the positive likelihood of manipulation or fraud in the pre-demise period.

In Panel C, we repeat these tests using as dependent variables *auditor-caught fraud*, *AAERs*, *restatements*, and *SCAC securities fraud*. In all even-numbered specifications, we control for industry crossed with year fixed effects, except for auditor-detected fraud whose small sample forces us to include only industry fixed effects. As in Panel B, the coefficient on the AA dummy is never positive and significant.

Krishnan and Visvanathan (2008) find that earnings management was more pronounced in the AA Houston office than in the Houston offices of other Big Five auditors. Since Enron was headquartered in Houston, this is not that surprising. Nevertheless, to address the concern that in certain regions AA audited firms may have been more likely to commit fraud, in Appendix Table A1, we restrict our sample to large corporations located in the state of Texas. For each AA client, we find a match among other Big Five clients within the two-digit SIC code, based on a propensity score to be an AA client. We generate the propensity score based on assets, sales, EBITDA, and leverage within industry. In Table A1 (columns 1 and 2), the dependent variable is the ProbM score. An AA dummy variable (equal to one for an AA client) is not significant either in the Texas sample (Panel A) or in the United States sample (Panel B). Across the remaining columns, we repeat the same tests using other measures of uncaught (*FScore*) and caught fraud *auditor-caught fraud*, *AAERs*, *restatements*, and *SCAC Securities Fraud*). The results are unchanged. We find no evidence that AA clients are statistically or economically different from other auditors' clients, consistent with Assumption 1.

II.3. Identification Assumption 2

Our methodology is based on the assumption that after the watershed date, AA clients were subject to an enhanced level of scrutiny not only by the new auditors, but also by gatekeepers, short sellers, investment intermediaries, and the media. This assumption implies that $Pr(caught|\, F, AA) > Pr(caught|\, F, \overline{AA})$. While we cannot test this inequality directly, the hypothesis is consistent with the decline in the stock price of AA clients at the announcement of AA problems (Chaney and Philipich (2002)) and indictment (Krishnamurthy, Zhou, and Zhou (2006)). Furthermore, – as we will show in Table 3 – this inequality is true in the data for all our definitions of fraud.

To obtain a point estimate on the amount of undetected fraud we further assume:

Assumption 2: $$Pr(caught|\, F, AA) = 1.$$

When it comes to purely financial fraud or financial restatements, Assumption 2 may be plausible. However, when we consider generic corporate fraud (including for instance price fixing), it is hard to imagine that in former AA clients all these types of frauds will be revealed. The reason is that some of the detectors with enhanced incentives (like the new auditors) have no role in uncovering these types of fraud. Thus for some types of fraud is more likely that $Pr(caught|\, F, AA) > Pr(caught|\, F, \overline{AA})$, but $Pr(caught|\, F, AA) < 1$, then – as we explain below – our estimate will yield an upper bound of the detection likelihood and a lower bound on the amount of undetected fraud.

In some cases (Kohlbeck, Mayhew, Murphy and Wilkins (2009) estimate 25% of the cases), AA clients switched audit firms but not audit partners. Instead, the former AA engagement partner moved to another audit firm, bringing the account. This continued relationship might reduce the new auditor's willingness to clean the dirty laundry; yet it is hard to imagine that it will completely eliminate the power of the experiment. Speaking about a firm that went from AA to Grand Thornton, the CEO of Grand Thornton testified at trial that "We converted it to a Grant Thornton audit approach and Grant Thornton audit-quality controls, and we had other people review the engagement."[9] Thus, even when the audit partner remains the same, the new audit firm performs an extra screening.

A more general concern is that the increased attention on corporate fraud that followed the Enron and WorldCom scandals might have prompted the SEC (or the other auditors not affected by the turnover) to become more active in detecting fraud. In the limit, if this enhanced scrutiny exposed all fraud in all firms, there will be no difference between the amount of fraud revealed in AA clients and the amount of

[9] https://www.wsj.com/articles/SB112951490246670395.

fraud revealed in clients of other audit firms, invalidating our experiment. Yet, as long as some enhanced scrutiny affects all firms, but AA firms are affected more, then our methodology will work, but will underestimate undetected fraud. Thus, our results should be interpreted as a lower bond on the pervasiveness of fraud.

Finally, the AA-demise was completely unexpected, so it could not have altered the ex-ante incentives to commit fraud. In this sense, it is different from a mandatory turnover, which is anticipated.

II.4. Conditional Probabilities within the AA Experiment

With Assumptions 1 and 2 in hand, we can use the law of conditional probability to derive an estimator for the detection likelihood of fraud. If we write down two versions of equation (1) (one for AA and one for non-AA), bringing the denominators to the other side, and dividing one by the other, we have a relationship that puts only observable detections of fraud on the right-hand side:

$$\frac{Pr(caught|\ F,\ \overline{AA}) \cdot Pr(F|\ \overline{AA})}{Pr(caught|\ F,\ AA) \cdot Pr(F|\ AA)} = \frac{\boldsymbol{Pr(F,caught|\ \overline{AA})}}{\boldsymbol{Pr(F,caught|\ AA)}}. \tag{2}$$

Substituting Assumptions 1 and 2 into the left-hand side of equation (2) implies:

$$\Pr(caught|F,\overline{AA}) = \frac{\boldsymbol{Pr(F,caught|\ \overline{AA})}}{\boldsymbol{Pr(F,caught|\ AA)}}. \tag{3}$$

Since the normal level of scrutiny is the one experienced by non AA clients, then $\Pr(caught|F,\overline{AA}) = \Pr(caught|F)$. Thus, Equation (3) provides an estimator for the detection likelihood of fraud that is based solely on two observables: the emergence of fraud in non-AA firms and the emergence of fraud in former AA firms.

Note that to the extent that not all fraud emerges in former AA clients (Assumption 2 becomes $Pr(caught|\ F,AA) < 1$), then our estimate $Pr(\ F)$ of the pervasiveness of fraud represents a lower bound of the real amount of fraud. To see this, consider that

$$\Pr(F) = \frac{\mathbf{Pr}\left(\mathbf{F},\mathbf{caught}\right)}{\Pr(caught\,|\,F)} > \frac{\mathbf{Pr}\left(\mathbf{F},\mathbf{caught}\right)}{\mathbf{Pr}\left(\mathbf{caught}\,|\,\mathbf{F}\right)},$$

where the inequality derives from (3) and $Pr(caught|\ F,AA) < 1$).

Note also that we derive the detection likelihood by comparing fraud detection in two groups (former AA clients and non-AA clients) at the same time. Thus, this estimate should not be affected by fluctuations in the probability of committing fraud, as long as these fluctuations are similar in the two groups. Yet, these fluctuations will matter for the level of fraud pervasiveness at any point in time, since this is likely to vary over the business cycle as shown by Wang et al. (2010).

II.5 Definitions

To implement the above methodology, we need a precise definition of the experiment. We define a company as having AA as an auditor if AA signed a financial report anytime in the calendar year 2001, irrespective of the firm's fiscal year. All companies without AA as auditor during this period are non-AA clients. Finally, we consider that a fraud was revealed during the detection period if the fraud started before the watershed date of November 30, 2001, and it came to light between the watershed date and the end of 2003 (the detection period). When we restrict our attention to U.S. incorporated firms with more than $750M in assets, which file at least one financial report during the detection period, we end up with 353 AA clients and 2404 non-AA clients. The number of detected fraud events in this window depends on the definition of fraud with the number of observations by fraud measure as follows: restatements (168), SCAC securities fraud (63), AAERs (59) auditor-detected (21).

III. Results

III.1 Main Detection Likelihood Results via AA Experiment

Table 3 reports the main detection likelihood estimates across the four measures of corporate fraud – *auditor-detected fraud*, *AAER*s, *restatements*, and *SCAC securities fraud*. To show that our results do not depend upon IPO-induced securities class actions, in Table 3 we also report *SCAC securities fraud* purged of IPO frauds. For each of these measures, we present the observed probability of a fraud being caught in the sample of former AA clients (column (1)) and former non-AA clients (column (2)), followed by (in column (3)) the t-test for the difference in the probability estimates of columns (1) and (2). Column (4) reports the ratio of columns (1) and (2), which per equation (3) represents our estimate of the detection likelihood.

First, note that across all measures, the frequency of fraud in former AA clients is higher than in former non-AA clients, validating the assumption that $\Pr(caught \mid F, AA) > \Pr(caught \mid F, \overline{AA})$, at least under Assumption 1 (i.e., $\Pr(F \mid AA) = \Pr(F \mid \overline{AA})$), for which we provided evidence in Table 2.

When we use the *auditor-detected fraud* measure, corporate fraud emerged in 2.0% of former AA clients and 0.6% of non-AA clients, with the ratio of these two numbers producing a 0.29 estimate for the detection likelihood. When we look at the individual cases, in all but one these frauds emerged after the change of auditor. For example, Peregrine Systems, Inc. switched from AA to KPMG on April 5th, 2002.[10] On May 6th, Reuter reports accounting inaccuracies involving up to $100 million in revenue. "The potential accounting inaccuracies were brought to the attention of Peregrine's audit committee by KPMG, which was hired in April to replace Arthur Andersen LLP as its auditors."[11] The only exception is McLeod USA, where the fraud emerges in the filing for prepackaged bankruptcy in early 2002.

For *AAERs*, corporate fraud emerged in 3.7% of former AA clients and 1.9% of non-AA clients, leading to a 0.52 detection likelihood. When we use restatements, the detection likelihood estimate is 0.34, with restatements in 14.5% of AA clients and 4.9% for non-AA clients.

For the *SCAC securities fraud* measure, corporate fraud emerged in 4.3% of former AA clients and 2.0% of non-AA clients, leading to a 0.47 detection likelihood. If we drop IPO-related class actions, the results are similar: 3.7% of fraud in former AA clients and 1.96% in non-AA clients, leading to a 0.53 detection likelihood. It is not surprising that there is higher detection likelihood using the *SCAC* measure, as the AA treatment increased scrutiny on firm financials and is least likely to expose other types of fraud, like failing to reveal material information.

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[10] https://www.forbes.com/2002/07/08/andersenarchive.html#69e9e2af438c.
[11] http://faculty.haas.berkeley.edu/morse/research/papers/Whistleblowers%20in%20US%20frauds%20final.pdf.

Note that our estimates are obtained from the ratio of the fraud caught in AA and non-AA firms. Thus, as long as the amount of fraud committed in AA and not AA clients respond to cyclical fluctuations in a similar fashion, our estimates are not affected by business cycle fluctuations in the *aggregate* level of fraud, an important phenomenon documented by Wang, Winton and Yu (2010).

These estimates provide a range for undetected frauds: from 29 to 52 out of every 100 committed frauds are caught, leaving between 48 to 71 of every 100 frauds undetected. Thus, despite the different sources and the different definitions of fraud, we find that a substantial amount of corporate fraud remains undetected. Yet, we can refine our estimates further. The assumptions outlined in Section 2 are unlikely to apply equally to all the four samples. For example, it is unlikely that scrutiny emerging from the AA demise will expose all the non-financial reporting fraud contained in the SCAC measure. The 0.47 detection likelihood is an upper bound of the true one, not an actual estimate. Similarly, the detection of an AAER-type of fraud depends on the willingness of the SEC to bring an enforcement action. In any economic analysis of crime and punishment (see Becker, 1968), the incentives of the SEC to bring a case against a defunct firm like AA are small. Thus, the 0.52 AAER estimate is also an upper bound.

By contrast, Assumption 2 is most likely to hold for frauds that auditors are most likely to catch, which applies to both the auditor-detected fraud and to accounting restatements. Thus, the estimate of the detection likelihood in which we have the most confidence is between 0.29 and 0.34, or 0.32. Roughly, one-third of corporate frauds that start are detected.

III.2. Detection Likelihood Robustness

It is possible that AA clients were in businesses intrinsically more prone to corporate fraud or its detection. One way to help to rule out this possibility is to observe these firms in a different time period and check that they are not behaving differently. To this purpose, we reproduce the same experiment comparing former AA and non-AA clients (minus a few firms that do not survive) in the two years after the detection period (i.e., 2004-2006) and measure fraud detection in these years. Since the enhanced scrutiny following the demise of AA cannot last forever, we regard this exercise as a placebo test. This placebo period coincides with the beginning of the implementation of SOX. A large literature has tried to establish what the effects of the introduction of SOX are (see Coates and Srinivasan (2014)). Our test, however, is unaffected by any impact of SOX, since it compares the detection rate in former AA clients and former non AA clients at the same time.

Table 3b reports the results. The percentage of firms caught committing fraud is statistically not different across former AA clients and former non-AA clients, suggesting that there is not a natural proclivity of former AA clients to commit more fraud. In addition, the similarity between the fraud revealed in AA and non-AA clients suggest that the enhanced disclosure of fraud during the treatment period is not just an acceleration of the discovery that would have taken place regardless (as hypothesized by Fang et al. (2016)), but a net increase in discovery.

In section *II.2,* we showed that AA had more clients in Communications & Transport, Refining & Extractive, Services & Healthcare, and Utilities, while less clients in Banks & Insurance, Retail & Wholesale and Computers. If – for unspecified reasons – corporate fraud was more prevalent among sectors in which AA was over-represented just prior to the detection period and not afterward, then our detection likelihood estimate could be biased. To address this concern, we report the detection likelihood estimates in various sub-samples that remove industries where AA was either over- or under-represented. (Appendix Table A2, Panels B and C report the industry and regional distribution of fraud for all the fraud measures.) As Table 4.A shows, the detection likelihoods remain substantially unchanged.

The same concern could arise from regional variation in AA clients. For this reason, in Table 4.B, we repeat the same exercise excluding some regions or some large states. Once again, the detection likelihood results appear stable.

III.3. Detection Likelihood Estimated via Bivariate Probit Framework of Wang (2013)

To validate our approach to estimate the iceberg of undetected fraud, we obtain an estimate of the detection likelihood following Wang's (2013) approach. Wang (2013) applies Poirier's (1980) partial observability bivariate probit model to estimate jointly the probability that a corporate fraud is started and the probability that it is caught, conditional on being started. The key identifying assumption is that factors exist that affect the probability of starting a fraud, but not the probability a fraud is revealed and vice-versa. Appendix III provides more details on identification in this model.

Following Wang (2013), we assume that the quantity of options held by the CEO and the importance of the CEO bonus as a fraction of the total compensation affect the likelihood of starting a fraud, but not the probability a fraud is revealed. By contrast, the level and volatility of past stock returns affect the probability a fraud is revealed, but not the probability a fraud is started. Higher volatility and lower returns are likely to promote detection. By contrast, these variables cannot affect the decision to start a fraud, since they were unknown at the time.

We include several variables motivated by the whistleblowers identified in DMZ. In particular, we include the number of analysts, the percentage of institutional ownership as a measure of short seller ability and therefore interest in the firm, and an indicator of whether a firm is in a so-called qui tam industry, where the government is a significant buyer of services. In a qui tam lawsuit, a whistleblower applies the False Claim Act, whereby individuals who blow the whistle on fraud against the government can recover payments in proportion to the size of the revealed fraud, once this is established in court. As DMZ show, in these industries employees are much more likely to blow the whistle on corporate fraud.

The variable definitions and summary statistics of all start and caught variables are presented in Appendix Table A3. In addition to the excluded variables of the start and caught equations and the high attention by whistleblowers variables, we also include firm covariates, as motivated by Wang (2013) and Wang, Winton and Yu (2010), including assets, R&D, leverage, return on assets (ROA), stock returns and stock volatility. For reasons of data limitations, we implement a simplified model relative to their work, focusing on the detection likelihood.

Table 5 reports our estimates of the bivariate probit. To highlight the benefit of the bivariate probit, we report also a simple probit of the likelihood a firm is revealed to have committed a fraud. We report both the point estimates and the marginal effect, computed at the sample mean.

The estimated effect of high whistleblowers' scrutiny is as expected. The number of analysts has a positive and significant coefficient in the caught equation and negative and significant coefficient in the start equation, consistent with the idea that a higher number of analysts has a deterrence effect on starting a fraud, but increases the probability that a fraud is revealed after it is started. Similarly, the dummy variable qui tam, which is equal to one if a company deals with public procurements and is subject to the False Claim Act, has a positive and significant coefficient in the caught equation and a negative and significant coefficient in the start equation of the bivariate probit. In qui tam industries with more scrutiny, frauds are much less likely to start (4.6 percentage points less) and more likely to be exposed (2.4 percentage point more likely). In both cases, the deterrence effect is bigger than the revelation effect.

The advantage of the bivariate probit is that it generates directly $\Pr(caught \mid F)$, i.e., the probability of a fraud being revealed conditional on having started. This can be inferred from the "caught" regression of the bivariate probit computed at the sample mean. The probability is 0.54, which compares with the detection likelihood estimates reported in section III.1.

An additional benefit of Wang bivariate probit is that it can help us support one of our key identifying assumptions. In its strictest form, Assumption 2 says that the forced audit turnover and the added scrutiny of former AA clients raised the probability of detection of an existing corporate fraud to 1. Using the bivariate probit model, we can focus on increased presence of incentives for whistleblowers. The model estimates imply that an increase of one standard deviation in the number of analysts would raise the probability of corporate fraud detection to 0.88. Likewise, being in a qui tam industry raises detection to 0.85. Both inferences are conditional on the effect of these variables on deterrence. Thus, an important punchline from this analysis is that while both these numbers are below one, they are not distant from one. In sum, the bivariate probit can give us a sense of how tight the lower bound is. We are going to apply this idea in the next section

IV. Pervasiveness: The Unconditional Probability of Engaging in Corporate Fraud

Having established the robustness of our detection likelihood estimates, we are now in the position to apply equation (1) to estimate the overall pervasiveness of corporate fraud.

IV.1 Fraud Pervasiveness Estimates

The numerator in equation (1) is the observable incidence of fraud that is caught, **Pr(*F, caught*)**. As Figure 1 shows, this number varies widely depending on the definition of corporate fraud and the time period of reference. Since fraud may be cyclical (Wang, Winton and Yu (2010)), we do not want to rely on a specific point in time, because this would affect the generalizability of our estimates. In Table 6, we use different time periods to capture both booms and busts. The start in January of 1998 and the end point in December of 2005 are both almost exactly halfway through the respective expansion periods, so the period covers one full business cycle from mid-point to mid-point. As a reminder, according to the NBER Business Cycle Dating Committee the two periods of expansion are March 1991- March 2001 and November 2001 – December 2007, while the one recession is March 2001-November 2001.

In Panel A we report the frequency of revealed corporate fraud depending on the definition of fraud and the time period. Auditor-detected fraud hovers around 1%, with a peak of 1.2% around 2000-2001. AAER-type of fraud averages 2.7% during the whole period 1998-2005, with a peak of 3.7% in the 2000-2001 period and a trough of 2.0% in 1998-99. Accounting restatements average 14.2% during the entire sample period, with a peak of 18.5% in 2002-3 and a trough of 13.2% in 1998-99. The broader SCAC securities fraud averages at 3.5%, with a peak of 5% in 2000-2001 and a trough of 2.9% in 1998-99.

We now are in position to report estimates of the pervasiveness of corporate fraud. The results are derived from equation (5): the observed frequency of caught fraud (Panel A) is divided by the detection likelihood (Panel B) to obtain the estimate of the pervasiveness of fraud (caught and uncaught) in different time periods.

As Panel C shows, not surprisingly the estimated pervasiveness of fraud differs significantly over the long period (1998-2005) for each of the four measures of corporate fraud. For example, financial reporting fraud based on AAERs varies between 3.9% and 7% with a mean of 5.2%. Our estimate of accounting fraud restatements varies between 22% and 54.8% with a mean of 42.1%.

Let us consider the different measures by focusing on the entire sample period (1998-2005). Auditor-detected fraud is a subcategory of securities fraud; thus it is not surprising that it has a frequency half as big as the SCAC measure (3.4% vs. 7.5%). In the same way, the AAER measure of fraud is more restrictive than the SCAC measure (as the AAER measure requires the SEC to act). For example, remember that the SEC failed to act on Madoff, despite six substantive complaints.[12] Thus, it is not surprising that the level of fraud defined as AAER is lower (5.2%) than that defined as SCAC (7.5%). By contrast, if we define fraud as an accounting infraction (*restatements*), the pervasiveness of fraud reaches 42.1%. Clearly, the average accounting violation is of a different severity than a securities fraud or a severe financial violation. It is not surprising that it is much more diffuse as a phenomenon.

If we look at the temporal fluctuations, we observe different patterns. In general, the period 2000-2001 gives the highest estimates of frequency of fraud, possibly as a result of the dot com bubble. By contrast, the estimates obtained from the entire sample period are remarkably similar to the estimates obtained from the most recent sample period (2004-2005). Thus, in the rest of the paper, we will use the average as a benchmark.

Thus far, we have not considered the fact that all detection likelihood ratios are upper bounds of the true detection likelihood, and some might be tighter than others. The type of fraud more likely to be revealed after a forced auditor turnover is financial fraud, especially financial fraud that is generally exposed by auditors. Thus, the probability that all fraud is revealed in former AA clients (Assumption 2) is more likely to hold for auditor-detected fraud and for financial restatements. Thus, the detection likelihood in those two cases (0.29 and 0.34) is likely to be a tighter upper bound.

When fraud is defined as AAER or SCAC securities fraud, Assumption 2 will be conservative. Thus, the detection likelihoods obtained using these types of fraud should be interpreted as looser upper

[12] https://www.nytimes.com/2009/09/03/business/03madoff.html.

bounds (i.e. less precise). To make them more comparable with the tighter upper bounds, we can use our results from Wang's bivariate probit. When a company is subject to the False Claims Act, the probability a fraud is revealed raises to 0.85, not 1. If we assume that AA forced turnover had the same effect, then equation (3) tells us that the detection likelihood ratio should be multiplied by $\Pr(caught \mid F, AA)$, i.e by 0.85. With this adjustment, the modified detection likelihoods become 0.44 for AAERS and 0.40 for SCAC securities, both closer to the one third estimate we obtained using financial frauds and restatements. By using this modification, the frequency of AAER type of fraud (detected and undetected) raises to 5.7% and the SCAC securities fraud estimate raises to 8.3%.

The fraud definition and the estimate used ultimately depend upon the scope of the exercise. For example, if we would want to evaluate the cost and benefits of the internal control systems introduced by the Sarbanes Oxley Act, we are interested in a broad definition of fraud. Internal controls are not meant to prevent just financial fraud, but any type of fraud. Thus, we would want to use the most comprehensive definition of fraud, i.e., the SCAC one, with a frequency of caught fraud over the longest sample period equal to 3.5%. Then, we want to apply the estimates of the detection likelihood that we know to be tighter, i.e., the ones derived using the auditor-detected fraud and financial restatements. If we apply the average of these two estimates, giving a detection likelihood of 0.32, to the SCAC definition we obtain the result that every year 11.2% of companies are involved in a major fraud.

IV.2. Comparison with Other Measures Present in the Literature

Our estimates of the level of fraud fall toward the lower end of the distribution of the estimates present in the literature.

Based on Beneish (1999), Beneish, Lee and Nichols (2013) build a model to predict financial fraud, able to predict 71% of the most famous accounting fraud cases that surfaced subsequent to the model's estimation period. The model flags 17.7% of firms as potentially fraudulent each year during the period 1997-2005.

Wang, Winton and Yu (2010) examine financial frauds among the 3,297 IPOs from 1995-2005. While their main goal is to show that fraud is procyclical, their bivariate probit model produces predicted probabilities of engaging in fraud of 10-15%, very much in line with our estimates.[13]

Prior to Lie (2005), no options backdating had been detected. Bebchuk, Grinstein and Peyer (2010) look back over this period and identify the percentage of publicly-traded firms from 1996-2005 in which CEOs or directors were 'lucky' directors in that they received option grants on day of the month the stock price was the lowest price. By their estimate 12.4% of firms have such lucky CEOs. Dichev, Graham, Harvey and Rajgopal (2013) survey 169 CFOs of public companies. Their survey suggests that 18.4% of firms manage earnings to misrepresent performance.

Finally, Zakolyukina (2018) uses a structural model to explore detected and undetected GAAP manipulation and reports that 73% of CEOs manipulate their financials, with this result dominated by undetected manipulation (she reports a detection likelihood of only 0.06).

V. How Expensive Is Corporate Fraud?

V.1 – Expected Cost of Fraud

To assess the economic relevance of corporate fraud is not sufficient to estimate how frequently fraud is occurring, we also need know how big the costs are when corporate fraud occurs. We do not innovate here, but we rely on existing estimates of the cost of fraud. As in the prior literature, we focus on the cost of fraud borne by the firms involved in fraud, ignoring spillovers to other firms. We build our calculations off two prior papers.

First, in an announcement-based exercise, KLM estimate the reputational loss of detected fraud at 25% of the equity value of the firm. This is almost entirely due to a loss in reputation, and captures the present value of the decline in expected cash flows as firms' investors, suppliers, and customers are expected to change the terms to interact with the firm.

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[13] We infer this from Figure 1, predicted probability of fraud, and summary statistics on the distribution of industry EPS growth available in the internet appendix.

KLM's cost estimates are for detected fraud and do not necessarily apply to undetected fraud. Even when a fraud is not yet in the public domain, the firm incurs costs for two reasons. First, the fraud is unlikely to remain a secret for customers and employees, who will seek business relationships or employment elsewhere, demand a premium to remain, or take advantage of the fraud themselves. For example, Bernie Madoff's employees like Frank Di Pasquale were lavishly paid to ensure their silence. In addition, they stole money for themselves.[14] Second, the biggest cost is often the cover up. For 20 years, Japanese company Olympus was able to hide a $730m financial loss incurred in 1990, with a series of bad acquisitions and accounting tricks. The bad acquisitions alone cost $300m.[15]

It is hard to put a number on these costs. Yet, if we assume that, at least in the medium term, the stock market is strong-form efficient, the abnormal low returns of companies that are likely to have committed a fraud, but were never exposed as fraudulent, can provide an estimate of these hidden costs. Beneish, Lee and Nichols (2013) perform this exercise. They compare the annual buy-and-hold return of firms with a high probM score with that of firms with a low probM score. After controlling for a four-factor model, they estimate an annual 10.9% difference in returns. We take this underperformance as an estimate of the costs of undetected fraud.[16]

We are now in the position to compute the total cost of fraud. Our estimates suggest that 11.2% of firms are committing fraud. If the detected fraud costs the firm 25% of market value and the undetected fraud costs 10.9%, then the cost of an average fraud is 15.4% of firm's market capitalization. Thus, the cost of fraud is 1.7% of firm's equity value per year (i.e. fraud pervasiveness (11.2%) * loss for fraud (15.4%)).

In 2004, the total capitalization of the U.S. equity market was $16 trillion.[17] Since on average 11.2% of firms are engaged in fraud, the annual fraud cost is $275 billion a year. If we repeat the calculation for 2018, the expected annual cost of fraud is $504 billion.

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[14] https://www.justice.gov/sites/default/files/usao-sdny/legacy/2012/04/16/20090811dipascaliinformationsigned.pdf.
[15] https://www.nytimes.com/2011/12/09/business/deep-roots-of-fraud-at-olympus.html
[16] We use Beneish et al.'s figures as the cost of undetected fraud, conditional on committing fraud.
If Beneish et al.'s numbers are both selection and treatment, they represent the unconditional effect of fraud, not the conditional one. In such a case, our method would underestimate the reputational cost of fraud.
[17] https://statistics.world-exchanges.org/.

V.2 – An Application to Cost-Benefit Analysis

When a firm is 100% owned by one individual, the cost of fraud is fully internalized by the owner. In publicly traded companies, where equity is dispersed and inside agents often own only a tiny fraction of the outstanding equity, this is not the case. These agency costs are one of the justifications for the introduction of regulations like Sarbanes Oxley (SOX). As an illustration of the wide applicability of our estimates, we sketch how it can be used for a cost-benefit analysis of SOX. Note that reducing agency costs is only one of the benefits of SOX. We are completely silent on the other potential benefit: reducing the lemon discount due to the asymmetry of information on the financial accounts.

Hochberg, Sapienza and Vissing-Jorgensen (2009) exploit survey data collected by Finance Executives International (FEI) to arrive to an estimate of \$3.8 million of compliance costs per firm, with costs increasing in the issuer's size.[18] To calculate the total compliance costs, we multiply this average compliance costs by the number of publicly traded firms in 2004 (5,226) to obtain an annual compliance cost of SOX of \$19.9 billion per year. Note that faced with a regulatory mandate to increase monitoring in some ways, firms may cut down some of the monitoring they were previously doing in other ways (Karpoff and Lott (1993)). Thus, \$19.9 billion represents an overestimate of SOX compliance costs.

The potential benefit of SOX is equal to the net reduction in the probability of fraud times the cost of fraud when it occurs. If instead of 11.2% of firms engaged in fraud, a policy change resulted in only 10.4% of firms engaged in fraud, the cost of fraud will drop by \$20 bn (0.8% times 15.4% (the average cost of fraud) times 16 trillion (the total equity market capitalization)). Thus, for the benefits of SOX to reduce its costs, it would suffice that SOX were able to reduce the probability of fraud by 0.8 percentage points (equal to 8% of the baseline probability).

Is it reasonable to assume that SOX could have that effect on the probability of fraud? In Table 5 we can see that the existence of a qui tam statute reduces the probability of starting a fraud by 4.6 percentage

[18] See Hochberg, Sapienza and Vissing-Jorgensen (2009), Table 11 on page 571 for the costs by size categories that we use in our estimates.

points. Thus, it would be strange that a much more sophisticated system of controls could not reduce the probability of starting a fraud by at least 0.8 percentage points.

VI. Conclusion

In this paper, we provide an estimation of the detection likelihood of fraud. We then can use this detection likelihood to quantify the pervasiveness of corporate fraud in the United States and assess the costs that this fraud imposes on society. The major problem in any such a study is how to estimate the amount of undetected fraud. We follow different approaches to infer the unconditional probability that a fraud is committed, regardless of whether it is subsequently caught. We find that only 1 in 3 frauds is detected. Using this estimate, we conclude that on average at any point in time over the business cycle, 42.1% of large public firms are intentionally violating accounting rules and 11.2% of the firms are committing securities fraud. Our estimate of the annual cost of this fraud using the 2004 market capitalization is $275 billion. If no improvement in the fraud governance or regulatory setting occurred, the 2018 cost of fraud would have been $504 billion.

These figures provide a pretty dismal picture of the effectiveness of governance in publicly traded U.S. companies. The large cost involved suggests that corporate fraud is a major component of the agency costs of public ownership. As a result, even expensive regulation, such as SOX, can be easily justified if it is able to reduce the probability that a fraud is committed even by a 0.8%.

Appendix I: Dyck, Morse, and Zingales (2010) Filters to Eliminate Frivolous Fraud

First, DMZ(2010) restrict attention to alleged frauds in the period of 1996 -2004, specifically excluding the period prior to passage of the Private Securities Litigation Reform Act of 1995 (PSLRA) that was motivated by a desire to reduce frivolous suits and among other things, made discovery rights contingent on evidence. Second, they restrict attention to large U.S. publicly-traded firms, which have sufficient assets and insurance to motivate law firms to initiate lawsuits and do not carry the complications of cross-border jurisdictional concerns. In particular, they restrict attention to U.S. firms with at least $750 million in assets in the year prior to the end of the class period (as firms may reduce dramatically in size surrounding the revelation of fraud). Third, they exclude all cases where the judicial review process leads to their dismissal.[19] Fourth, for those class actions that have settled, they only include those firms where the settlement is at least $3 million, a level of payment previous studies suggested to divide frivolous suits from meritorious ones.[20] Fifth, they exclude those security frauds that Stanford classifies as non-standard, including mutual funds, analyst, and IPO allocation frauds.[21] The final filter removes a handful of firms that settle for amounts of $3 million or greater, but where the fraud, upon their reading, seems to have settled to avoid the negative publicity.[22]

[19] They retain cases where the reason for dropping the suit is bankruptcy for in this instance the cases could still have had merit but as a result of the bankruptcy status, plaintiff lawyers no longer have a strong incentive to pursue them.

[20] Grundfest (1995), Choi (2007) and Choi, Nelson, and Pritchard (2009) suggest a dollar value for settlement as an indicator of whether a suit is frivolous or has merit. Grundfest establishes a regularity that suits which settle below a $2.5 -$1.5 million threshold are on average frivolous. The range on average reflects the cost to the law firm for its effort in filing. A firm settling for less than $1.5 million is most almost certainly just paying lawyers fees to avoid negative court exposure. To be sure, we employ $3 million as our cutoff.

[21] Stanford Class Action Database distinguishes these suits for the reason that all have in common that the host firm did not engage in wrongdoing. IPO allocation cases focus on distribution of shares by underwriters. Mutual fund cases focus on timing and late trading by funds, not by the firm in question. Analyst cases focus on false provision of favorable coverage.

[22] The rule they apply is to remove cases in which the firm's poor ex post realization could not have been known to the firm at the time when the firm or its executives issued a positive outlook statement for which they are later sued.

Appendix II: Calculation of Beneish's Probability of Manipulation Score (ProbM Score)

The components in the ProbM Score include days sales in receivables, gross margin, asset quality index, sales growth index, depreciation index, SGA index, leverage, and the ratio of accruals to assets. (Please refer to Beneish (1999) for motivation of how each of these subindices captures an aspect of manipulation.) To construct the ProbM Score, we use Compustat, data to construct the variable components following Beneish (1999) and apply his estimated coefficients.

The probability of manipulation, ProbM Score, of Beneish (1999) is calculated as follows:

$$\begin{aligned}\text{ProbM} = {} & -4.84 + 0.92 * \text{DSR} + 0.528 * \text{GMI} + 0.404 * \text{AQI} + 0.892 * \text{SGI} + 0.115 * \text{DEPI} \\ & + 0.172 * \text{SGAI} + 4.679 * \text{ACCRUALS} - 0.327 * \text{LEVI}\end{aligned}$$

The variable codes are defined as follows:

DSR = Days Sales in Receivables

GMI = Gross Margin Index

AQI = Asset Quality Index

SGI = Sales Growth Index

DEPI = Depreciation Index

SGAI = Sales, General and Administrative expenses Index

ACCRUALS - Total Accruals to total assets

LEVI = Leverage Index

Appendix III – Partial Observability Bivariate Probit Estimates of Detection Likelihood

Let E_{it} be the incentive for firm i to engage in fraud at time t. Fraud is committed if E_{it} is positive:

$$\begin{aligned} E_{it} &= X_{it}^{E}\Gamma_{E} + \mu_{it} \\ engage_{it} &= 1 \ if\, E_{it} > 0. \end{aligned} \tag{11}$$

E_{it} is a function of observables X_{it}^{E}, which includes incentives and opportunities indicators.

Identification in Poirier's model comes from two pieces. First, Poirier assumes that $\left(\mu_{it}, \nu_{it}\right)$ are distributed bivariate standard normal. Second, identification depends on the ability to come up with variables which affect either firms' incentives to engage in fraud or detectors' ability to uncover fraud, but not both. Under the assumption that some of the X_{it}^{E} and some of the X_{it}^{D} are excluded from each other's set, the parameters in Γ_{E} and Γ_{D} can be identified using a bivariate probit model:

$$Pr\left(engage_{it}, caught_{it} \middle| X_{it}^{E}, X_{it}^{D}\right) = \Phi\left(X_{it}^{E}\Gamma_{E},\, X_{it}^{D}\Gamma_{D}\right), \tag{12}$$

where $\Omega(\cdot,\cdot)$ denotes joint cumulative standard normal distribution over the two arguments.

The abnormal stock return included in Table 5 affect the likelihood of detection, but not the likelihood of engaging in fraud as they would not be known at the time when a firm started to engage in fraud. In Table 5 we include two types of variables that we assume influence the likelihood of engaging in frauds but not detection. First, we include compensation-related measures as prior papers have found option grants to be an important predictor of fraud (e.g. Burns and Kedia (2006), Efendi, Srivastava and Swanson (2007)). We use Execucomp's valuation of all of the options held by top executives. We also measure the incentives provided by their most recent pay package to focus on future as opposed to current performance as captured in percentage of restricted stock grants divided by total compensation. Second, we include measures of market conditions under the assumption that the starting of frauds may be procyclical. Wang, Winton and Yu (2010) review theoretical bases for procyclicality in fraud and provide some evidence that positive sentiment (captured by IPO conditions) has positive, albeit non-linear, association with the likelihood to start committing fraud.

References

Agrawal and Chada, (2005), "Corporate Governance and Accounting Scandals." *Journal of Law and Economics*.

Baker, M. and J. Wurgler, (2006), "Investor Sentiment and the Cross-Section of Stock Returns," *Journal of Finance* vol. 61, p.1645-1680.

Bebchuk, Lucien, Olav Grinstein and Urs Peyer, (2010). "Lucky CEOs and Lucky Directors," *Journal of Finance*, (65): 2363-2401.

Becker, Gary S., 1968, "Crime and Punishment: An Economic Approach," Journal of Political Economy, Vol. 76, No. 2 (Mar. - Apr.), pp. 169-217.

Beneish, M.D., (1999), "The Detection of Earnings Manipulation, *Financial Analysts* Journal, 24-36.

Beneish, M. D., Lee, C. M. C., & Nichols, D. (2013). Earnings manipulation and expected returns. Financial Analysts Journal, 69(2), 57-82.

Berger, Philip G. and Eli Ofek. (1995). "Diversification's Effect on Firm Value." *Journal of Financial Economics*, vol. 37(1), 39-65.

Blouin, J., B. Grein, B. Rountree, (2005). "An analysis of forced auditor rotation: the case of former Arthur Andersen clients." *Accounting Review*.

Burns, N. and S. Kedia. (2006). "The impact of performance-based compensation on misreporting." *Journal of Financial Economics* 79: 35-67.

Cahan and Zhang, (2006). "After Enron: Auditor Conservatism and Ex-Andersen Clients." *The Accounting Review*, 81: 49-82

Chen, Ken Y. and Jian Zhou. (2007). "Audit Committee, Board Characteristics and Auditor Switch Decisions by Andersen's Clients." *Contemporary Accounting Research*, 24 (4): 1085-1117.

Choi, Stephen J. (2007), "Do the Merits Matter Less after the Private Securities Litigation Reform Act?" *Journal of Law, Economics and Organization,* 23 (3): 598-626.

Choi, Stephen J., Karen K. Nelson and A.C. Pritchard. (2009). "The Screening Effect of the Securities Litigation Reform Act." *Journal of Empirical Legal Studies,* 6(1): 35-68.

Coates John C. and Suraj Srinivasan, 2014, "SOX after Ten Years: A Multidisciplinary Review", *Accounting Horizons*, September 2014, Vol. 28, No. 3, pp. 627-671

Coates IV, John C., 2015, Cost-Benefit Analysis of Financial Regulation: Case Studies and Implications, *124 Yale Law Journal* 882 (2015).

Coffee, John C. (1986). "Understanding the Plaintiff's Attorney: The Implications of Economic Theory for Private Enforcement of Law through Class and Derivative Actions," *Columbia Law Review*, (86): 669-727.

Coffee, John C. (2006), *Gatekeepers: The Professions and Corporate Governance,* Oxford University Press: New York.

Dechow, P. M., R. G. Sloan, and A. Sweeney. (1996). "Causes and consequences of earnings manipulation: An analysis of firms subject to enforcement actions by the SEC." *Contemporary Accounting Research,* 13 (1): 1-36.

Dechow, Patricia M., Weili Ge, Chad R. Larson, Richard G. Sloan, 2011, Predicting Material Accounting Misstatements," *Contemporary Accounting Research, 28: 17–82.*

Dichev, Ilia, Joh Graham, Campbell Harvey and Shiva Rajgopal, (2013). "Earnings Quality: Evidence from the Field," Working paper,

Dyck, Alexander, Adair Morse and Luigi Zingales. (2010). 'Who Blows the Whistle on Corporate Fraud?" *Journal of Finance*. 65 (6): 2213-2254.

Dyck, Alexander, Natalya Volchkova, and Luigi Zingales (2008), "The Corporate Governance Role of the Media: Evidence from Russia," *Journal of Finance,* 63 (3): 1093-1136.

Efendi, Jap, Anup Srivastava, and Edward Swanson, (2007). "Why Do Corporate Managers Misstate Financial Statements? The Role of in-the-money Options and Other Incentives," *Journal of Financial Economics*, 85(3): 667-708.

Eisenberg, Macey, (2004). *"*Was Arthur Andersen Different? An Empirical Examination of Major Accounting Firm Audits of Large Clients" *Journal of Empirical Legal Studies,*

Fang, Vivian W. , Allen H. Huang, Jonathan M. Karpoff, 2016, "Short Selling and Earnings Management: A Controlled Experiment," Volume71, Issue3, June 2016, Pages 1251-1294.

Feroz, E., K. Parek and V. Pastena, (1991). "The Financial and Market effects of the SEC's Accounting and Auditing Enforcement Releases," *Journal of Accounting Research,* 29: 107-148.

General Accounting Office, 2003, "Public Accounting Firms. Required Study on the Potential Effects of Mandatory Audit Firm Rotation," United States General Accounting Office, 2003.

General Accounting Office, "Audits of Public Companies: Continues Concentration in Audit Market for Large Public Companies Does Not Call for Immediate Action'," United States General Accounting Office, 2008.

Grundfest, Joseph A. (1995). "Why Disimply?" *Harvard Law Review*, (108): 740-741.

Hennes, K, Leone, A., B. Miller, (2008). "The Importance of Distinguishing Errors from Irregularities in Restatement Research: The Case of Restatements and CEO/CFO Turnover," *The Accounting Review*, 83(6): 1487-1519.

Hochberg, Yael V., Paola Sapienza and Annette Vissing-Jorgensen. 2009. A Lobbying Approach to Evaluating the Sarbanes-Oxley. *Journal of Accounting Research*. 47(2): 519-583.

Jensen, Michael and William Meckling, (1976). "The Theory of the Firm: Managerial Behavior, Agency Cost, and Ownership Structure." *Journal of Financial Economics* 3, no. 4 (October): 305-60

Karpoff, J.M. and J.R. Lott, Jr., (1993). "The Reputational Penalty Firms Bear from Committing Criminal Fraud." *Journal of Law and Economics,* (36): 757-802.

Karpoff, Jonathan M., D. Scott Lee, and Gerald S. Martin, (2008). "The Cost to Firms of Cooking the Books," *Journal of Financial and Quantitative Analysis* 43 (3): p. 581–612.

Karpoff, Jonathan, Allison Koester, D. Scott Lee and Gerald Martin, (2017). "Proxies and databases in financial misconduct research," The Accounting Review, November 2017, Vol. 92, No. 6, pp. 129-163.

Kealey, Burch T, Ho Young Lee, and Michael T. Stein (2007) The Association between Audit-Firm Tenure and Audit Fees Paid to Successor Auditors: Evidence from Arthur Andersen. Auditing: A Journal of Practice & Theory: November 2007, Vol. 26, No. 2, pp. 95-116.

Kempf, Elisabeth and Spalt, Oliver G., 2019. Litigating Innovation: Evidence from Securities Class Action Lawsuits. European Corporate Governance Institute - Finance Working Paper

Krishnamurthy, S, J Zhou, N Zhou, 2006, "Auditor Reputation, Auditor Independence and the Stock Market Impact of Andersen's Indictment on Its Client Firms," Contemporary Accounting Research 23 (2), 465-490, 2006.

Krishnan, Gopal V., (2007). "Did earnings conservatism increase for former Andersen clients?" *Journal of Accounting, Auditing an*d *Finance*. 22(2): 141-163.

Lie, Eric (2005), "On the Timing of CEO Stock Option Awards." *Management Science*, 51(5): 802-812.

Miller, Gregory S.(2006). "The Press as a Watchdog for Accounting Fraud." *Journal of Accounting Research* 44(5): 1001-1033.

Nagy, Albert L. (2005) Mandatory Audit Firm Turnover, Financial Reporting Quality, and Client Bargaining Power: The Case of Arthur Andersen. Accounting Horizons: June 2005, Vol. 19, No. 2, pp. 51-68.

Palmrose, Z.-V.; V. Richardson; and S. Scholz,. (2004). "Determinants of Market Reactions to Restatement Announcements." *Journal of Accounting and Economics* 37: 59–89.

Palmrose, Z-V., and S. W. Scholz. (2004). "The circumstances and legal consequences of non-GAAP reporting: Evidence from restatements." *Contemporary Accounting Research*. 21 (1): 139-180.

Povel, Paul, Rajdeep Singh and Andrew Winton, 2007. "Booms Busts and Fraud," *Review of Financial Studies*, (20): 1219-1254.

Roe, Mark, (2002), "Corporate Law's Limits." *Journal of Legal Studies*, 31:.

Soltes, Eugene F., (forthcoming), "The Frequency of Corporate Misconduct: Public Enforcement versus Private Reality Journal of Financial Crime (forthcoming).

Wang, Tracy Yue, (2013). "Corporate Securities Fraud: Insights from a New Empirical Framework", *Journal of Law, Economics and Organization*, 29 (3): 535-568.

Wang, Tracy Yue, Andrew Winton and Xiaoyun Yu, (2010). "Corporate Fraud and Business Conditions: Evidence from IPOs," *Journal of Finance,*

Yu, Frank (2008). ''Analyst Coverage and Earnings Management,'' *Journal of Financial Economics (88):* 245–71.

Zakolyukina, Anastasia, (2018) "How Common Are Intentional GAAP Violations? Estimates from Dynamic Model," *Journal of Accounting Research*. 56(1). March 2018.

FIGURE 1: Frequency of Observed Corporate Fraud

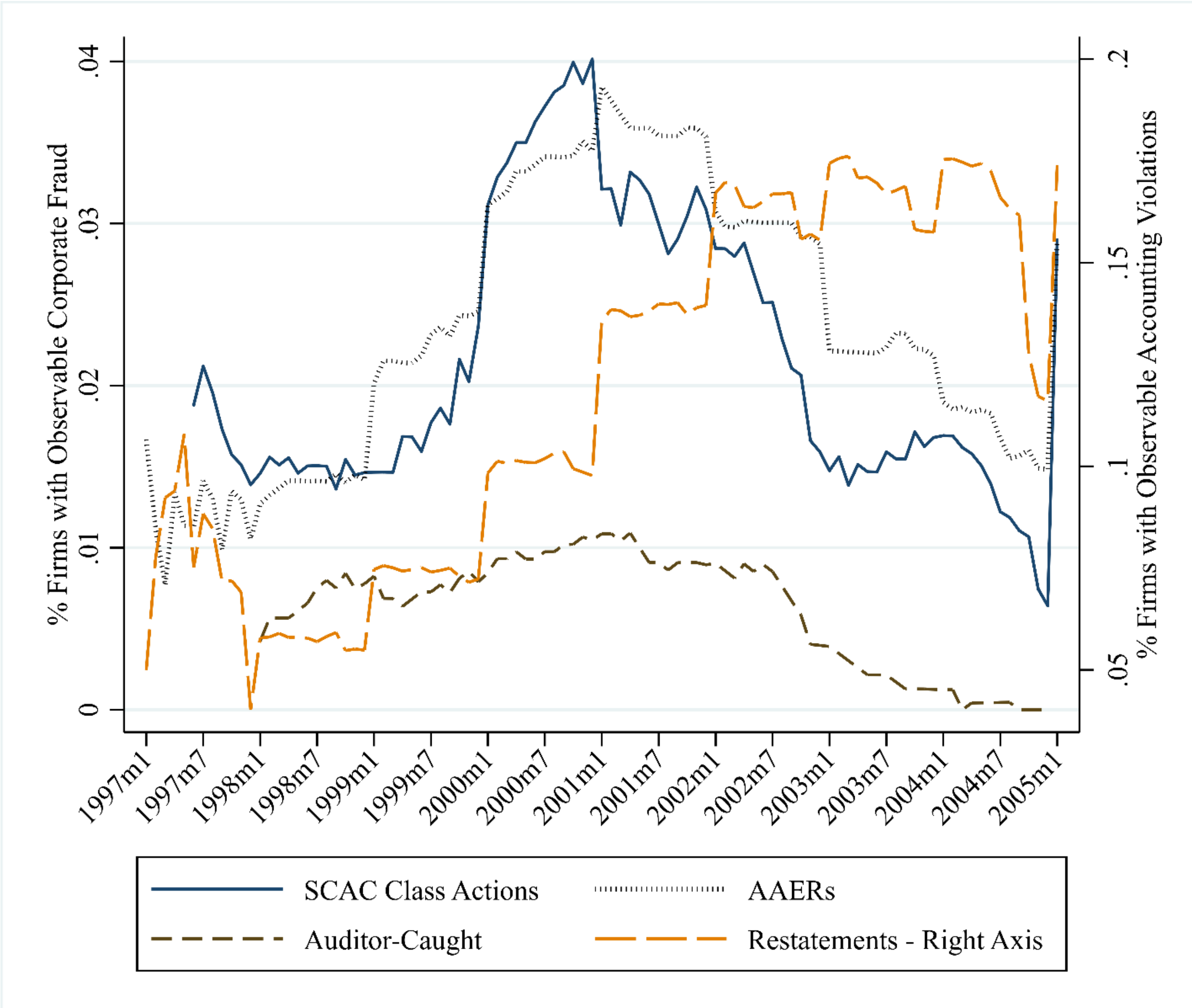

FIGURE 1: Frequency of Observed Corporate Fraud

Plotted are the prevalence rates of corporate fraud, for cases of corporate fraud that are eventually caught. The magnitudes represent the percentage of all U.S. large public corporations committing corporate fraud that is caught. Auditor-detected frauds are frauds in the DMZ (2010) sample of SEC 10(b) securities class actions which were triggered by an auditor, either by an auditor resignation or by the auditor issuing a qualified opinion and either the firm or analysts revealing the fraud. Restatements are from AuditAnalytics and refer to restatements triggered by accounting misapplication. AAERs are the SEC investigation releases used in Dechow, et al. (2011). The sample SCAC securities fraud is from Kempf-Splat (2019). Restatements are plotted with magnitudes on the right scale.

Table 1: Statistics: Arthur Andersen Clients (AA) and Non-AA Clients, 1998-2000

The sample is all Compustat firms with $750 million in assets in the 1998-2000 period. The designation of auditor is the calendar time designation in financial statements, not the experiment designation starting in Table 3. All statistics are collapsed to a single observation per firm, except where a firm switches auditors per the column desingation. In those cases, we allow the firm to appear in multiple columns. Because of this time series collapsing, we have more AA firms here than in the experiment tables. In Panel A, the p-values are from ttests for the mean comparisons, and the z-values are from ranksum tests for the medians. Leverage is long term debt divided by assets. In Panel B, we present the industry distribution of firms and present Pearson distribution equivalence tests.

Panel A: Firm Characteristics

	AA Firms Observations = 483		All Non-AA Observations = 1,792				Big 5 Non-AA Observations = 1,426			
	Mean	Median	Mean	p-value	Median	z-value	Mean	p-value	Median	z-value
Assets	6,998	1,991	9,802	0.120	1,982	0.920	9,088	0.148	2,040	0.594
Sales	3,645	1,471	4,297	0.212	1,384	0.784	4,431	0.144	1,433	0.593
EBITDA	568.6	196	668.9	0.318	182	0.174	677	0.233	201	0.794
Leverage	0.34	0.311	0.279	0.000***	0.256	0.000***	0.279	0.00***	0.260	0.000***

Panel B: Industry Distribution

	AA Firms Observations = 483 Percent of Distribution (*100)	All Non-AA Observations = 1792 Percent of Distribution (*100)	Big 5 Non-AA Observations = 1,426 Percent of Distribution (*100)
Agriculture	0.41	0.17	0.14
Banks & Insurance	12.42	21.09	19.57
Chemicals	3.11	4.58	4.70
Communication & Transport	16.15	10.44	9.40
Computers	4.35	10.04	9.68
Durable Manufacturing	10.35	12.39	13.32
Food & Tobacco	1.24	2.85	2.59
Lumber, Furniture, Printing	4.14	4.30	4.42
Mining & Construction	2.07	1.56	1.68
Pharmaceuticals	1.66	2.90	3.16
Refining Extractive	3.93	1.79	1.82
Retail & Wholesale	7.25	9.49	9.33
Services & Healthcare	11.39	7.37	7.36
Textile & Apparel	1.04	1.06	0.98
Utilities	20.50	9.99	11.85
	100	100	100
Pearson's Chi-Square test of Distribution Equivalence of non-AA Samples to AA Sample			
Statistic		105.2	85.8
P-value		0.000	0.000

Table 2: Did Arthur Andersen Clients Exhibit Excess Corporate Fraud in the Pre-period of 1998 - 2000?

Panel A: Univariate tests: Probability of manipulation scores (ProbM Score) are calculated using Compustat data following Beneish (1999), winsorized at 0.025 for extremes outside Beneish's range. Fraud score (FScore) are from Dechow-Ge-Larson-Sloan (2011), auditor-caught frauds are from Dyck-Morse- Zingales (2010), AAERS are from the CFRM at Berkeley-Haas, accounting restatements are from AuditAnalytics, SCAC are from Kempf-Splat (2019). The designation of auditor is the calendar time designation in financial statements. Panel A reports cross sectional t-test of differences in mean fraud rates, comparing 1998-2000 large corporations with AA as auditor to all others, or to those with another Big 5 auditor.

	AA Firms		All Non-AA		p-value	Big 5 Non-AA		p-value
	Mean	Obs.	Mean	Obs.		Mean	Obs.	
ProbM Score (Beneish)	-1.711	435	-1.548	1,603	0.014 **	-1.601	1,269	0.096
ProbM > -2.2 threshold	0.585	435	0.624	1,603	0.078 *	0.613	1,269	0.217
Fscore (Dechow, et al 2011)	3.217	420	4.378	1,559	0.301	3.664	1,246	0.650
Fscore > 1.4 threshold	0.323	420	0.413	1,559	0.000 ***	0.391	1,246	0.005 ***
Auditor-Caught Fraud	0.0186	483	0.0201	1,792	0.839	0.021	1,426	0.747
AAERs	0.0352	483	0.0458	1,792	0.313	0.0463	1,426	0.302
Restatements	0.164	483	0.137	1,792	0.134	0.139	1,426	0.183
SCAC Securities Fraud	0.0704	483	0.0854	1,792	0.287	0.0799	1,426	0.498

Panels B & C: Multivariate Tests: The dependent variables are accounting scores predicting fraud (Panel B) or realized corporate fraud (panel C). Columns (3), (6), (9) and (12) used indicators for the score being above the relevant threshold of concern as identified in the original literature. Industry fixed effects, when included, are those of Table 1. Estimation is either by ordinary least squares (OLS) or by logit, as designated. ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively. Standard errors in brackets are clustered at the firm level.

Panel B: Unobservable Measures of Fraud Dependent Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent var.:	Accounting Manipulation (ProbM Score)						Fraud Score (FScore)					
Estimation:	OLS ProbM	OLS ProbM	Logit ProbM>-2.2	OLS ProbM	OLS ProbM	Logit ProbM>-2.2	OLS FScore	OLS FScore	Logit FScore >1.4	OLS FScore	OLS FScore	Logit FScore >1.4
Arthur Andersen	-0.142***	-0.0224	0.11	-0.104*	0.00648	0.158	-0.384	0.179	0.0229	-0.155	0.318	0.0683
	[0.0514]	[0.0509]	[0.0960]	[0.0530]	[0.0518]	[0.0990]	[0.516]	[0.546]	[0.120]	[0.515]	[0.554]	[0.124]
Log Assets	-0.106***	-0.0938***	-0.109***	-0.112***	-0.106***	-0.113***	-0.184	0.00543	0.0411	-0.0758	0.117	0.0663
	[0.0164]	[0.0157]	[0.0341]	[0.0176]	[0.0166]	[0.0371]	[0.277]	[0.266]	[0.0388]	[0.296]	[0.283]	[0.0428]
Sales / Assets	0.352***	0.115**	0.366***	0.342***	0.121**	0.364***	-1.025***	-1.608***	-0.0978	-0.772***	-1.252***	-0.0859
	[0.0411]	[0.0498]	[0.108]	[0.0427]	[0.0512]	[0.117]	[0.252]	[0.373]	[0.0806]	[0.246]	[0.356]	[0.0879]
EBITDA / Sales	-2.495***	-2.849***	-3.155***	-2.394***	-2.604***	-3.345***	-23.28***	-22.19***	-2.909***	-19.25***	-17.70***	-3.280***
	[0.332]	[0.390]	[0.623]	[0.360]	[0.426]	[0.700]	[4.199]	[4.779]	[0.565]	[4.143]	[4.566]	[0.650]
LT Debt/Assets	-0.189	-0.107	0.00651	-0.234	-0.145	-0.203	-7.047***	-5.010***	-0.345*	-5.521***	-3.355***	-0.432*
	[0.141]	[0.145]	[0.188]	[0.156]	[0.157]	[0.209]	[1.486]	[1.208]	[0.209]	[1.481]	[1.147]	[0.236]
Sample	All Clients			Clients of Big 5 Auditors			All Clients			Clients of Big 5 Auditors		
Year F.E	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y
Industry*Year FE	N	Y	N	N	Y	N	N	Y	N	N	Y	N
Observations	4,963	4,963	4,963	4,167	4,167	4,167	4,855	4,855	4,855	4,121	4,121	4,121
R2/ Pseudo R2	0.082	0.18	0.123	0.085	0.193	0.125	0.031	0.066	0.172	0.025	0.061	0.183

Table 2 (Continued)

Panel C: Observable Measures of Fraud Dependent Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent var.:	Auditor-Caught Securities Fraud				AAERs			
Non-AA sample:	--	--	Big 5	Big 5	--	--	Big 5	Big 5
Estimation:	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Arthur Andersen	-0.0375	0.158	-0.0865	0.0369	-0.143	0.0227	-0.145	-0.0213
	[0.395]	[0.426]	[0.397]	[0.430]	[0.290]	[0.306]	[0.297]	[0.313]
Log Assets	0.547***	0.619***	0.540***	0.594***	0.471***	0.562***	0.460***	0.536***
	[0.106]	[0.122]	[0.117]	[0.130]	[0.0884]	[0.0910]	[0.0965]	[0.0967]
Sales / Assets	0.297*	0.0184	0.282*	0.0406	0.419***	0.309**	0.425***	0.330**
	[0.152]	[0.212]	[0.167]	[0.215]	[0.103]	[0.131]	[0.110]	[0.138]
EBITDA / Sales	-0.883	-1.898	-1.494	-2.163	-0.409	-0.925	-0.653	-0.99
	[2.324]	[1.431]	[2.286]	[1.472]	[1.043]	[0.910]	[1.152]	[1.014]
LT Debt/Assets	0.715	0.873	0.305	0.368	0.48	0.879*	0.259	0.612
	[0.728]	[0.775]	[0.860]	[0.846]	[0.489]	[0.477]	[0.558]	[0.510]
Fixed Effects:								
Industry	N	Y	N	Y	N	Y	N	Y
Year	Y	Y	Y	Y	Y	Y	Y	Y
Industry*Year	N	N	N	N	N	Y	N	Y
Observations	5,465	4,993	4,641	4,228	5,465	5,105	4,641	4,331
R-squared	0.0586	0.103	0.0597	0.117	0.062	0.109	0.0602	0.0989

	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Dependent var.:	Restatements				SCAC Securities Fraud 10b-5			
Non-AA sample:	--	--	Big 5	Big 5	--	--	Big 5	Big 5
Estimation:	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Arthur Andersen	0.119	0.189	0.127	0.181	-0.103	0.0118	-0.076	0.023
	[0.149]	[0.156]	[0.153]	[0.160]	[0.208]	[0.221]	[0.213]	[0.226]
Log Assets	-0.104*	-0.0548	-0.0818	-0.0428	0.127**	0.243***	0.141*	0.255***
	[0.0541]	[0.0550]	[0.0584]	[0.0585]	[0.0627]	[0.0676]	[0.0730]	[0.0775]
Sales / Assets	0.109	-0.0824	0.0979	-0.0836	-0.0947	-0.234	-0.0934	-0.205
	[0.0769]	[0.106]	[0.0875]	[0.117]	[0.116]	[0.157]	[0.129]	[0.167]
EBITDA / Sales	-1.208*	-1.359*	-1.214*	-1.193	-4.751***	-5.059***	-4.158***	-4.224***
	[0.643]	[0.711]	[0.713]	[0.784]	[1.154]	[1.268]	[1.251]	[1.442]
LT Debt/Assets	-0.0784	0.0165	0.0233	0.0821	-0.810**	-0.231	-0.878*	-0.206
	[0.262]	[0.281]	[0.293]	[0.310]	[0.411]	[0.406]	[0.478]	[0.461]
Fixed Effects:								
Industry	N	Y	N	Y	N	Y	N	Y
Year	Y	Y	Y	Y	Y	Y	Y	Y
Industry*Year	N	Y	N	Y	N	Y	N	Y
Observations	5,465	5,465	4,641	4,641	5,465	5,237	4,641	4,152
R-squared	0.0133	0.0402	0.0134	0.0388	0.0493	0.114	0.0434	0.11

Table 3: Detection Likelihood Estimates from the Arthur Andersen Experiment

Panel A presents main estimates of the detection likelihood using the AA experiment. The sample is U.S. publicly traded corporations with more than $750 million in assets. A firm is identified as being an Arthur Andersen (AA) client if it was audited by AA in the year 2001. In all cases, the frauds considered are those starting prior to the watershed date of December 1, 2001, which are caught after the watershed date and before the end of 2003. Auditor-detected frauds are frauds in the DMZ (2010) sample of class action frauds which were detected by an auditor either by an auditor resignation or by the auditor issuing a qualified opinion and either the firm or analysts revealing the fraud. Restatements are from AuditAnalytics and refer to restatements triggered by accounting mis-application. AAERs are the SEC investigation releases used in Dechow, et al. (2011). The sample SCAC Securities Fraud is from Kempf-Splat (2019). The first two columns report the probabilities that a firm commits a corporate fraud and is caught. The third column reports p-values for the t-test of the equivalence of these probability estimates. The final, right hand column reports the detection likelihood, calculated as the ratio of the left two columns under the experiment identification. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level. Panel B reproduces the experiment for the former AA clients, but using a placebo detection period of 2004 to 2006, without restricting when the corporate fraud starts.

Panel A: Main Experiment

	Probability a firm stared a fraud before the test period and is caught *Pr(fraud, caught)*			*Detection Likelihood*
	AA (obs=353)	Non-AA (obs=2404)	p-value	Caught period: November 2001-December 2003
Severe Financial Reporting Violations				
Auditor-Detected Frauds	0.0198	0.0058	0.0047	0.294***
AAERs: DGLS	0.0368	0.0191	0.0320	0.520**
Accounting Violations				
AuditAnalytics Restatements	0.1445	0.0487	0.0000	0.337***
Securities Fraud at large				
SCAC Securities Fraud	0.0425	0.0200	0.0082	0.470***
SCAC, No IPOs	0.0368	0.0196	0.0378	0.531**

Panel B: Caught Time Placebo

	Pr(fraud, caught)			*Detection Likelihood*
	AA (obs=314)	Non-AA (obs=2150)	p-value	Caught period: 2004 - 2006
AAERs: DGLS	0.0191	0.0191	0.9963	0.998
AuditAnalytics Restatements	0.1656	0.1874	0.3518	1.132
SCAC Securities Fraud	0.0318	0.0205	0.1983	0.643

Table 4: Detection Likelihood Robustness to Industry and Region Subsampling

The table presents estimates of the detection likelihood using the AA experiment by industry and region filtering. The overall sample is U.S. publicly traded corporations with more than $750 million in assets. Industries and regions are excluded, as noted in the rows. All detection likelihood estimates are calculated as in Table 3. The variation in estimates result from excluding industries as noted. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level from p-value t-tests of the difference in caught fraud probabilitis by AA or non-AA.

Panel A: Robustness in Excluding Industries

	AA Test Firms	Detection Likelihood			
		Auditor Detected	AAERs	Restatements	SCAC
Full Sample (Table 3)	353	0.294***	0.520**	0.337***	0.470***
<u>Excluding Less Represented Industries</u>					
Banks & Insurance	313	0.295**	0.608	0.355***	0.544*
Computers	340	0.329**	0.593	0.320***	0.468**
Retail &Wholesale	332	0.276***	0.458**	0.313***	0.456***
<u>Excluding More Represented Industries</u>					
Refining & Extractive	338	0.286***	0.496**	0.327***	0.481**
Communication &Transport	306	0.594	0.656	0.357***	0.524**
Utilities	276	0.229***	0.536*	0.374***	0.499**
Services & Health	313	0.237***	0.426***	0.334***	0.425***

Panel B: Robustness in Excluding Regions and States

	AA Test Firms	Detection Likelihood			
		Auditor Detected	AAERs	Restatements	SCAC
Full Sample (Table 3)	353	0.294***	0.520**	0.337***	0.470***
<u>Excluding Regions:</u>					
Southeast	267	0.277**	0.615	0.353***	0.396***
Northeast	290	0.398	0.385***	0.311***	0.525*
Midwest	258	0.247***	0.523*	0.399***	0.553
Mountain	333	0.266***	0.496**	0.349***	0.430***
Southwest	307	0.249***	0.537*	0.301***	0.422***
West	323	0.365**	0.568*	0.316***	0.529**
<u>Excluding Large States:</u>					
Texas	320	0.253***	0.549*	0.323***	0.442***
California	328	0.358**	0.558*	0.310***	0.519**
New York	335	0.306**	0.460**	0.338***	0.507**

Table 5: Bivariate Probit Estimates of the Conditional Probability of Detection

The table presents two estimation, labeled as (1) and (2) in columns. Model (1) is a probit estimation of the probability of a firm being caught in any severe financial fraud. In both models, severe financial corporate fraud is defined as either AAERs or auditor-detected fraud. Model (2) is a partial observability bivariate probit estimation of Wang (2013), where the system estimates the probability of starting and catching fraud, conditional on starting. Both the coefficient and marginal effects are reported. For both equations, variables include firm specific variables including log of assets, lof of R&D expense, leverage, accounting performance (ROA), firm-specific stock market performance (Return) and the variability of stock returns (Standard Dev. Return). In addition, all specifications include three variables from DMZ (2010) that reflect the intensity of the scrutiny of fraud detectors, which may have a significant impact on detection or in the threat of detection as a prevention. These variables are the log count of analysts following the firm, the degrees of shortability (institutional ownership percentage), and whether the firm is in a qui tam applicable industry. For the start equation, included are also two measures about CEO compensation measures that potentially affect the likelihood of starting a fraud (log options value (a stock of expsoure to the firm) and lagged options compensation relative to total compernsation (a meausureof immediate bonus pressure). The caught equations include market-wide variables which may predict the climate for detection, including the S&P500 return, the current year VIX as well as the change in VIX relative to last year, and finally the sum of the groosss settlements on securities class action cases. Standard errors clusterd at the firm level are in brackets. ***, **, and ** denote significance at the 1%, 5%, and 10% levels.

	(1) Probit		(2) Bivariate Probit			
	Caught		Start		Caught	
	Coefficient	Marginal Probability	Coefficient	Marginal Probability	Coefficient	Marginal Probability
Ln Analyst Estimates (lag)	0.268***	0.0040	-2.679***	-0.0686	3.398***	0.0404
	[0.0899]		[0.842]		[0.902]	
Lag Shortability	-0.0026	0.0000	0.00599	0.0002	-0.0092	-0.0001
	[0.00180]		[0.00527]		[0.00615]	
Qui Tam	-0.00797	-0.0001	-1.777**	-0.0455	2.056***	0.0244
	[0.167]		[0.713]		[0.754]	
Ln Assets (lag)	0.120***	0.0018	1.123***	0.0287	-0.696***	-0.0083
	[0.0340]		[0.276]		[0.244]	
Ln R&D (lag)	0.0434***	0.0007	0.145**	0.0037	-0.157**	-0.0019
	[0.0163]		[0.0667]		[0.0636]	
Leverage (lag)	0.517**	0.0078	-4.429***	-0.113*	4.949***	0.0588
	[0.224]		[1.459]		[1.550]	
ROA (lag)	0.205	0.0031	3.546**	0.0908	0.173	0.0021
	[0.540]		[1.534]		[1.578]	
Return (lag)	-0.195*	-0.0029	-0.318	-0.0081	0.957***	0.0114
	[0.103]		[0.211]		[0.263]	
Standard Dev Return (lag)	0.0147	0.0002	8.533**	0.2180	-7.826*	-0.0930
	[0.0865]		[3.954]		[4.221]	
Ln Options Held ($)			-0.139***	-0.0036		
			[0.0443]			
Bonus as % of Compensation (lag)			1.424**	0.0365		
			[0.684]			
S&P 500 Return	-0.260	-0.0039			-0.233	-0.0028
	[0.240]				[0.683]	
Change in VIX	-0.129***	-0.0019			-0.0542	-0.0006
	[0.0396]				[0.112]	
VIX Current Year	0.202***	0.0030			0.163	0.0019
	[0.0462]				[0.128]	
Ln Gross Settlements	0.187**	0.0028			-0.378*	-0.0045
	[0.0864]				[0.201]	
Observations	8567		6286			
Chi-square	113.2		31.8			

Table 6: How Pervasive is Corporate Fraud?

The table presents estimates of corporate fraud pervasiveness in publicly traded US firms with more than $750 million in assets, along with the inputs to generate these estimates. Panel A presents the average likelihood a firm is engaging in corporate fraud sometime in monthly data during the date range specified by columns and by the corporate fraud measure in the rows. (The corporate fraud observed percentages in Panel A are all corporate frauds, not just those aligning with the AA experiment timing.) Panel B presents the detection likelihoods from Table 3. Panel C uses the Panels A and B estimates to calculate the prevasiveness of corporate fraud as the observed fraud divided by the detection likelihood. Panel D adds the bivariate probit extension; our AA experiment Assumption 2 requires that all frauds of former AA clients are caught, but the bivariate probit estimates suggest that only 0.85 of frauds are caught in high scrutiny environments. Thus, Panel D adjusts accordingly. Panel E presents our best estimate, using the SCAC observable fraud prevalence from Panel A and the average detection of the severe financial reporting frauds (the average of 0.294 and 0.337), and displaying without and with the bivariate probit adjustment.

Panel A: Annual Ongoing Corporate Fraud Eventually Caught as % of Firms

	All		*1998-1999*	*2000-2001*	*2002-2003*	*2004 -2005*
Financial Reporting (Auditor-Detected)	1.00%	[n=56]	1.07%	1.21%	0.71%	--
Financial Reporting (AAERs)	2.69%	[n=141]	2.01%	3.66%	2.69%	2.38%
Accounting Fraud (Restatements)	14.19%	[n=793]	7.40%	13.21%	18.47%	17.67%
Securities Fraud (SCAC)	3.52%	[n=283]	2.89%	4.97%	2.93%	3.29%

Panel B: Detection Likelihood Estimates from Table 3

	Detection Likelihood
Financial Reporting (Auditor-Detected)	0.294
Financial Reporting (AAERs)	0.520
Accounting Fraud (Restatements)	0.337
Securities Fraud (SCAC)	0.470

Panel C: Pervasiveness of Corporate Fraud Estimates

	Fraud Pervasiveness = Observed Fraud / Detection Likelihood				
	All	*1997-1999*	*2000-2001*	*2002-2003*	*2004 -2005*
Financial Reporting (Auditor-Detected)	3.4%	3.7%	4.1%	2.4%	--
Financial Reporting (AAERs)	5.2%	3.9%	7.0%	5.2%	4.6%
Accounting Fraud (Restatements)	42.1%	22.0%	39.2%	54.8%	52.4%
Securities Fraud (SCAC)	7.5%	6.1%	10.6%	6.2%	7.0%

Panel D: Pervasiveness of Corporate Fraud Estimates under Bivariate Probit Adjustment

	*Fraud Pervasiveness = Observed Fraud / (Detection Likelihood * 0.85)*
	All
Financial Reporting (AAERs)	6.1%
Securities Fraud (SCAC)	8.8%

Panel E: Best Estimate of Pervasiveness of Corporate Fraud

	SCAC: Annual Ongoing Observable Corporate Fraud	*Detection Likelihood*	*Best Estimate of the Pervasiveness of Corporate Fraud*
Securities Fraud (SCAC)	3.5%	31.6%	11.2%

Appendix Table A1: Propensity Score Matched, Collapsed Tests: Were AA Clients Committing Corporate More Fraud in the Pre-Period?

The sample is a cross section of firms with $750 million in assets and a Big 5 auditor during 1998-2000. Estimation in Panel A is limited to only Texas headquartered firms. Panel B replicates panel A for the entire United States. Estimation is a propensity-matched estimation. For each AA client firms, we find a non-AA match in the same two digit SIC code, matched on the propensity of assets, sales/assets, EBITDA/sales and leverage to predict being an AA client. Once matched, the dependent variables are measures of uncaught fraud (columns 1-4) or caught fraud (columns 5-12) as follows: the probability of manipulation score (prob-M score) of Beneish (1999) (columns 1-2), fraud score (Fscore) of Dechow, et al (2011) (columns 3-4), auditor-detected fraud suits (DMZ) (columns 5-6), AAERS (columns 7-8), AuditAnalytics accounting restatements (columns 9-10), and SCAC Securities Fraud from Kempf-Splat (2019). All regressions include industry fixed effects (SIC2) and year fixed effects. ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively. Robust (for OLS) standard errors are in brackets.

Panel A: Texas Only Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Manipulation (ProbM)		Fraud Score (Fscore)		Auditor-Detected		AAERs		Restatements: Acctng.		SCAC Securities Fraud	
Arthur Andersen	0.206	0.183	0.302	0.769	0.0179	0.0144	0.0446	0.0393	0.0446	0.0463	0.0179	0.0158
	[0.242]	[0.230]	[1.908]	[1.702]	[0.0177]	[0.0140]	[0.0399]	[0.0352]	[0.0605]	[0.0601]	[0.0215]	[0.0190]
Log Assets		-0.0697		-0.492		0.0178		0.0223		0.017		0.0092
		[0.0796]		[0.737]		[0.0168]		[0.0272]		[0.0318]		[0.0114]
Sales / Assets		0.163		-0.952		-0.00122		-0.00826		-0.0251*		-0.00538
		[0.0997]		[1.501]		[0.00238]		[0.0101]		[0.0138]		[0.00447]
EBITDA / Sales		-4.224***		-37.74*		0.0815		-0.454**		-0.186		-0.119
		[1.311]		[19.61]		[0.0794]		[0.223]		[0.300]		[0.104]
LT Debt/Assets		-0.644		-22.19		0.0616		-0.200**		0.0756		-0.0944
		[0.783]		[13.58]		[0.0577]		[0.0918]		[0.142]		[0.0819]
Observations	161	161	164	164	188	188	188	188	188	188	188	188
R-squared	0.005	0.089	0.000	0.101	0.009	0.053	0.011	0.077	0.005	0.021	0.005	0.032

Panel B: United States Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Manipulation (ProbM)		Fraud Score (Fscore)		Auditor-Detected		AAERs		Restatements: Acctng.		SCAC Securities Fraud	
Arthur Andersen	-0.00318	-0.0155	-0.191	-0.098	0.00347	0.00458	-0.00867	-0.00732	0.0191	0.0197	-0.00433	-0.00236
	[0.0752]	[0.0711]	[0.717]	[0.715]	[0.00532]	[0.00546]	[0.0107]	[0.0107]	[0.0173]	[0.0173]	[0.0109]	[0.0108]
Log Assets		-0.118***		-0.215		0.0145***		0.0229***		-0.000107		0.0103
		[0.0273]		[0.351]		[0.00536]		[0.00774]		[0.00794]		[0.00643]
Sales / Assets		0.296***		-0.466		0.0055		0.0202**		0.00387		-0.00274
		[0.0567]		[0.373]		[0.00472]		[0.00939]		[0.0116]		[0.00568]
EBITDA / Sales		-3.601***		-25.31***		-0.0697*		-0.0976		-0.253**		-0.360***
		[0.604]		[8.869]		[0.0396]		[0.0615]		[0.123]		[0.0949]
LT Debt/Assets		-0.131		-6.316**		0.0182		0.0173		0.0104		-0.0422
		[0.200]		[2.841]		[0.0151]		[0.0274]		[0.0465]		[0.0320]
Observations	1,628	1,628	1,640	1,640	1,937	1,937	1,937	1,937	1,937	1,937	1,937	1,937
R-squared	0	0.097	0	0.031	0	0.026	0.001	0.025	0.001	0.006	0	0.027

Appendix Table A2: Industry and Region of Corporate Fraud Cases in Experiment

The sample is U.S. publicly traded corporations with more than $750 million in assets. Auditor-detected frauds are frauds in the DMZ (2010) sample of class action frauds which were detected by an auditor either by an auditor resignation or by the auditor issuing a qualified opinion and either the firm or analysts revealing the fraud. 'Restatements are from AuditAnalytics and refer to restatements triggered by accounting mis-application. AAERs are the SEC investigation releases used in Dechow, Ge, Larson and Sloan (2011). SCAC are securities fraud class actions from Kempf-Splat (2019). In all cases, the frauds considered are those starting prior to the watershed date of October 31, 2001 and being detected before the end of 2003 period. Panel A presents cross-sectional correlations. Panel B and C report fraud incidence by industry or geography.

Panel A: Correlations among Fraud Measures

	Auditor Detected	AAER	Restatements	SCAC
	Sample: 2757 firms (1 observation per firm) over the period 11/2001-12/2003			
Severe Financial Reporting Violations				
Auditor-Detected Frauds	1.000			
AAERs: DGLS	0.152	1.000		
Restatements				
AuditAnalytics Restatements	0.104	0.129	1.000	
Securities Fraud at large				
SCAC Securities Fraud	0.348	0.190	0.120	1.000
	*Note: All Correlations are statistically significant at < 1% level			

Panel B: Corporate Fraud Incidence by Industry

	Auditor Detected	AAER	Restatements	SCAC
	Sample: 2757 firms (1 observation per firm) over the period 11/2001-12/2003			
Agriculture	--	--	0.5%	--
Banks Insurance	33.3%	24.8%	24.0%	24.6%
Chemicals	--	--	2.4%	1.5%
CommunicationTransport	20.8%	12.0%	12.9%	13.1%
Computers	8.3%	15.4%	9.8%	14.6%
Durable Manufacturing	--	9.4%	5.8%	3.1%
Food Tobacco	--	2.6%	3.7%	--
Lumber Furniture Printing	--	1.7%	1.1%	3.8%
Mining Construction	--	--	2.1%	--
Pharmaceuticals	6.3%	1.7%	1.3%	10.0%
Refining & Extractive	--	0.9%	2.9%	3.1%
Retail & Wholesale	4.2%	12.0%	9.8%	2.3%
Services & Health	8.3%	10.3%	5.5%	3.1%
Textile Apparel	--	--	1.8%	--
Utilities	18.8%	9.4%	16.4%	20.8%
Total	100%	100%	100%	100%

Panel C: Corporate Fraud Incidence by Region

	Auditor Detected	AAER	Restatements	SCAC
	Sample: 2757 firms (1 observation per firm) over the period 11/2001-12/2003			
Midwest	17%	26%	25%	25%
Mountain	4%	2%	6%	5%
Northeast	33%	30%	21%	34%
Southeast	29%	20%	15%	15%
Southwest	13%	10%	16%	12%
West	4%	12%	17%	8%
Territories	--	--	1%	--
Total	100%	100%	100%	100%

Appendix Table 3: Variable Definitions and Summary Statistics for Bivariate Probit

Panels A and B present, respectively, the high attention to detection variables and the firm covariates, both used in the start and detection probit estimates. Panels C and D, respectively, present the variables used in the start equation only or the caught equation only in the bivariate probit estimation.

Panel A: High Attention to Detection Variables

Variable	Description	Source	Mean	SD
Log Analyst Coverage	Log of the number of analyst covering the firm +1.	I/B/E/S	2.076	0.757
Shortability	Institutional shareholding, in percentage of shares.	Compact-D	48.97	27.80
Qui-Tam Industry	An indicator for the firm's industry being one in which qui tam lawsuits are possible. Included are healthcare and defense contractor industries.	Civil Division, Dept. of Justice	0.042	0.201

Panel B: Covariates for Detecting Fraud

Variable	Description	Source	Mean	SD
Log Assets	Log of total book assets ($million)	Compustat	8.086	1.263
Log R&D	Log R&D expenditures +1 (in $million)	Compustat	0.646	1.794
Leverage	Long term debt/ total assets	Compustat	0.254	0.216
ROA	Operational income after depreciation / total assets	Compustat	0.064	0.082
Stock Return	Return on firm stock	CRSP	0.164	0.636
Standard Dev. Return	In-sample monthly standard deviation of firm stock.	CRSP	0.112	0.377

Panel C: Variables to Predict Staring Fraud, but not Catching Fraud, in the Bivariate Probit

Variable	Description	Source	Mean	SD
Log Options Held	The sum of the in-the-money exercisable options for all executives.	Execucomp	7.683	3.500
Incentive Pay %	The average of the ratio of restricted stock grants divided by total compensation across executives for a firm-year.	Execucomp	0.398	0.236

Panel D: Variables to Predict Catching Fraud, but not Starting Fraud, in the Bivariate Probit

Variable	Description	Source	Mean	SD
S&P 500 Return	S&P Index return	CRSP	0.082	0.193
Innovation to VIX	1-year percentage change in VIX	CRSP	-0.356	3.991
VIX	Implied volatility of S&P 500 index options	CRSP	23.195	3.512
Log Settlements	Log of annual settlements from SEC enforcement	SEC	7.187	1.424