Fraud culture

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ABSTRACT

We develop a measure of the culture of fraud. The measure is constructed using machine learning to predict security class action lawsuits based on eight dimensions of corporate culture—adaptability, community, customer-oriented, detail-oriented, integrity, openness, results-oriented, and teamwork—computed from the text of employee reviews. The fraud culture measure combines dimensions of corporate culture in the most predictive way with the accuracy exceeding the predictive ability of firm size, growth, and profitability. Fraud culture mostly varies with openness, adaptability, and the extent to which culture is customer- and detail-oriented. Fraud culture is stable over time, although it has temporarily declined around the implementation of the Dodd-Frank Act. Fraud culture is slow to change. For CEO turnover, the potential for change is muted by matching; thereby CEOs join firms with the culture similar to their previous firm.

PRELIMINARY DRAFT
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1. Introduction

Corporate culture is believed to be important for firm outcomes. Culture is ranked the highest among "the things that contribute to long-term firm value" by executives (Graham et al., 2022); and a large consulting practice on culture assessments and advice exists (Chatman and O'Reilly, 2016). Despite the importance of culture, it has proven difficult to define and measure many dimensions of culture with the corresponding difficulties in mapping culture to firm outcomes. This paper focuses on one such outcome—securities fraud—that historically has been costly to both investors and firms.[1] We develop a measure of fraud culture that builds on commonly studied dimensions of corporate culture and describes firms in which fraud is more likely to occur. We examine the evolution of fraud culture and its potential to change with CEO turnover.

Culture matters for corporate wrongdoing. Norms and values shared by employees can affect both incentives to commit fraud and perceived risks of doing so. Lo (2016) refers to the Gordon Gekko effect, "greed is good," in that culture transmits negative values and makes malfeasance much more likely. For example, as one of Enron's employees put it, "Our job was to take advantage of the law to make as much money as we can." (Dallas, 2003) Enron was expecting their employees to work around the rules, encouraging extreme competition through a highly political reward system with little tolerance for differing views. The forces of shared norms could also make committing fraud more

[1] According to the Stanford Law School Securities Class Action Clearinghouse and Cornerstone Research, the average number of securities class action filings was 192 with the average maximum dollar losses at $1,083 billion over 1997–2022. From Cornerstone Research (2024), the maximum dollar losses measure "the dollar-value change in the defendant firm's market capitalization from the trading day with he highest market capitalization during the class period to the trading day immediately following the end of the class period."

costly. Because employees are more likely to observe wrongdoing, they are also the ones who are most likely to report on fraud (Dyck et al., 2010).[2] Thus, a culture of openness and transparency can mitigate the risk of wrongdoing going unreported.

Culture has been notoriously difficult to measure. One of the contributing factors has been disagreement about the definition of culture. In reviewing culture research, Chatman and O'Reilly (2016) suggest to define culture as "[...] as the norms that characterize a group or organization that, if widely shared and strongly held, act as a social control system to shape members' attitudes and behaviors." The focus on shared norms has determined measurement choices in the literature. Most of the literature has relied on surveys and interviews (e.g., O'Reilly et al., 2014; Graham et al., 2016, 2022; Makridis, 2018), but also firm disclosure such as corporate websites (e.g., Guiso et al., 2015b), employee reviews (e.g., Grennan, 2019; Graham et al., 2022), and conference calls (e.g., Li et al., 2021).

We overcome the difficulty of measuring culture by identifying relevant discussion in employee reviews from the company review website Glassdoor. Using reviews provides an unobtrusive measure for a large sample of firms, which is important given the rare nature of fraud. As shared norms, this paper uses eight dimensions of culture commonly considered in the literature (e.g., O'Reilly et al., 2014; Guiso et al., 2015b; Graham et al., 2016, 2022; Li et al., 2021). These dimensions are adaptability, community, customer-oriented, detail-oriented, integrity, openness, results-oriented, and teamwork. We measure the extent to which these norms are mentioned in the reviews' pros and cons. Looking at the pros and cons separately captures both high and low manifestations of the same norm. We follow Cong et al. (2019) in using textual factors to identify these dimensions.

[2] In Dyck et al. (2010), the parties playing a key role in detecting fraud are employees (17% of the securities class action cases), non-financial-market regulators (13%), and the media (13%).

This approach creates clusters in the space of word embeddings from `word2vec` (Mikolov et al., 2013a,b,c). We center these clusters around seed words selected manually based on meaning, i.e., `word2vec`-based synonyms, for a given corpus of pros or cons reviews. The seed words are chosen separately for pros and cons because the word usage depends on the polarity of the description. After creating meaningful clusters, we compute exposure of each firm-year to each of the 16 clusters with two clusters per cultural norm.

Having measures of cultural norms, we use machine learning to combine these norms in the most predictive way to identify fraud. We define fraud based on securities class action lawsuits data (e.g., Dyck et al., 2010, 2023). The firm-year is labeled as fraudulent if it overlaps with the class period. That is, the time period for which investors alleged wrongdoing and sue the firm in the lawsuit under Rule 10b-5 claims or Section 11 of the Securities Act of 1933. The use of machine learning allows for interactions between different cultural norms in predicting fraud, e.g., fraud culture can be described by the interaction of results-oriented culture in non-transparent environments. Relying on the criterion of out-of-sample predictive ability for constructing the fraud culture measure imposes tougher requirements than an in-sample development and evaluation of a measure (Freedman, 1991; Hofman et al., 2021). Overfitting data in-sample is easy, especially with a large number of variables and rare outcomes, whereas the out-of-sample test gets closer to describing a robust pattern of predictive variation in the data.

We compare the out-of-sample prediction accuracy of models that include measures of cultural norms only against an uninformed baseline and a model that includes firm size, growth, and profitability with and without these norms included. Uninformed baseline assigns the probability of a firm-year to be fraudulent to an average frequency of a fraudulent firm-year based on training data. We use contemporaneous variables to predict fraud. We find the culture-norms models outperform both an uninformed baseline and financial-variables models. Adding culture norms to financial-variables models improves prediction accuracy. We use predictions from the culture-norm models as a measure of fraud culture. That is, fraud culture measure combines firms' cultural norms in the most predictive way to identify fraud. While all culture norms enter the measure, fraud culture mostly varies with openness, adaptability, and the extent to which culture is customer- and detail-oriented.

Our sample period covers 2008—2017. The fraud culture measure changes little over time with a small temporary drop coinciding with the Dodd-Frank Act. The Dodd-Frank Act, enacted in 2010, implemented a number of governance and whistleblower provisions that can affect fraud occurrence, such as clawbacks on incentive compensation, independence of compensation committees, and whistleblower incentives and protection. Fraud culture varies by industry. Health care scores the highest on fraud culture. Telecommunications and manufacturing have the next highest fraud culture. The lowest fraud culture is in retail, chemicals, and consumer durables. As for individual culture norms, health care is low on customer-oriented culture, low integrity, and low openness, which is consistent with its highest fraud culture. Whereas retail is high on customer-oriented culture, low on detail-oriented culture, but not as low on adaptability and openness, which is consistent with its lowest fraud culture.

Firm leadership is believed to have power to change corporate culture, including fraud culture. We examine CEO turnover data to test whether incoming CEOs make a difference. There is evidence of matching and convergence on fraud culture. That is, incoming CEOs match to firms with similar fraud culture to their previous firms and culture in the firm the incoming CEO joins converges to the culture the incoming CEO brings. Both of these findings can be driven by the patterns in CEO turnover; that is, CEOs tend to stay in the same industry with culture being similar for the firms within the same industry.

By developing the measure of fraud culture, we contribute to the literature in a number of ways. First, we contribute to the literature that attempts to predict fraud and factors that contribute to it. This literature has relied on different measures of fraud such as SEC Accounting and Auditing Enforcement Releases (AAERs) (e.g., Beneish, 1999; Dechow et al., 2011), financial statement restatements (e.g., Zakolyukina, 2018; Bertomeu et al., 2021), securities class action lawsuits (e.g., Dyck et al., 2023), and violations of laws and regulations (e.g., Campbell and Shang, 2022). The conclusion is that it is a difficult prediction task, especially when the attempt is being made to do that in real time (Bao et al., 2020, 2022). Traditionally, the literature has studied fraud using financial variables with more recent literature adding non-financial variables such as deception cues (Larcker and Zakolyukina, 2012), CEO traits (Davidson et al., 2015), and the text of employee reviews from Glassdoor (Campbell and Shang, 2022). While we have a different outcome from Campbell and Shang (2022) who rely on violations of laws and regulations, we focus on the discussion of specific cultural norms in employee reviews. By contrast, Campbell and Shang (2022) use word counts and text-based methods to project text on outcomes, which allows them to identify misconduct-related words—a smaller unit than topics of cultural norms.

Second, there is a large and growing literature on culture and whether it matters. This literature is mostly focused on firm performance and value (e.g., Guiso et al., 2015b; Graham et al., 2022; Green et al., 2019). For instance, Guiso et al. (2015b) find that values proclaimed by firms are irrelevant for firm's performance; but, when top managers are perceived as trustworthy and ethical, performance is stronger. In Graham et al. (2022), the survey-based measure of culture is positively associated with Tobin's Q. Corporate wrongdoing has also been considered. Biggerstaff et al. (2015) identify unethical culture by CEOs who systematically backdate their option grants and/or exercises. Liu (2016) measures corruption culture by the cultural background of officers and directors, showing that high corruption culture is associated with misconduct. A number of papers consider financial reporting quality and earnings management as an additional outcome (e.g., Li et al., 2021; Graham et al., 2022). By contrast to this literature, we attempt to develop a measure of fraud culture by combining cultural norms in the most predictive way to identify fraud.

Third, it has been difficult to measure culture, and literature has leveraged several approaches. A number of papers used surveys and interviews (e.g., O'Reilly et al., 2014; Graham et al., 2016, 2022), personal experience of executives and directors of the firm (e.g., Davidson et al., 2015; Biggerstaff et al., 2015; Liu, 2016), ratings of culture by external parties or by employees (e.g., Guiso et al., 2015b; Ji et al., 2017; Green et al., 2019; Zhou and Makridis, 2019), firm disclosures on corporate websites and conference calls (e.g., Guiso et al., 2015a; Li et al., 2021), and the text of employee reviews (e.g., Corritore et al., 2018; Grennan, 2019). We contribute to this literature by extracting culture norms from employee reviews similar to Grennan (2019) and Li et al. (2021), although our text-analysis approaches differ in that we use seeded clusters in the space of word embeddings. We further combine these often-studied dimensions of culture to a single measure of fraud culture.

2. Corporate culture

2.1 Definition of corporate culture

There are many definitions of corporate culture, which also makes it difficult to study. Different researchers can study different constructs and label them "culture." Chatman and O'Reilly (2016) suggest research has developed predictive (or empirical) validity without construct validity because of the lack of common definition. As they describe, predictive validity is a variable's ability to predict outcomes as predicted by a theory; whereas construct validity a variable's ability to measure what it claims to be measuring. Because culture is unobserved, establishing construct validity of culture measures has been much more difficult than showing predictive validity. In reviewing culture research, Chatman and O'Reilly (2016) suggest to define culture as "[...] as the norms that characterize a group or organization that, if widely shared and strongly held, act as a social control system to shape members' attitudes and behaviors." They further describe these norms can be assessed on (1) *content*, i.e., what is deemed important, (2) *intensity*, i.e,. how important the norm is, and (2) *consensus*, i.e., how widely shared the norm is.

2.2 Measuring corporate culture

This paper measures corporate culture from employee reviews by identifying the discussion of culture norms. By doing so, we attempt to follow the definition of norms and their dimensions proposed by Chatman and O'Reilly (2016). For *content* of the norms, we follow prior research by considering eight norms (e.g., O'Reilly et al., 2014; Guiso et al., 2015b; Graham et al., 2016, 2022; Li et al., 2021). These are adaptability, community, customer-oriented, detail-oriented, integrity, openness, results-oriented, and teamwork. For instance, O'Reilly et al. (2014) obtain six of these norms, except for community and openness, using factor analyses of the revised the Organizational Culture Profile from O'Reilly et al. (1991), which was developed to evaluate organizational norms with a set of value statements that characterize an organization. The two values of community and openness were identified by Guiso et al. (2015b) when analyzing the advertised values on S&P 500 firms' websites. There are no strict definitions for each of these norms. Instead, the literature characterized each norm by a set of descriptors or value statements that capture each norm, e.g., using ethics, accountability, trust, honesty, responsibility for the norm of integrity. For *intensity* and *consensus* about the norms, we rely on the properties of discussion in employee reviews. That is, if the norm is important and widely shared, employees will discuss it frequently in their reviews. Thus, presence and the extent of the discussion capture all three dimensions of culture to some extent.

2.3 Culture norms associated with fraud

There is no such norm as "fraud culture." Instead, the literature has described a number of features of workplaces with higher propensity of fraud (e.g., Dallas, 2003; Raftery and Holder, 2014; Association of Certified Fraud Examiners, 2016). These features can be mapped to culture norms. The norm of integrity, sometimes referred to as culture of ethics and compliance, is considered the most important in the context of fraud. High ethical standards are expected to directly prevent unethical or illegal behavior. The norm of openness and a related norm of adaptability, including openness in communication and flexibility of adaptable firms that can enhance the flow of information, can increase the visibility of wrongdoing and make it easier to report the violation. The norms of teamwork and community, including fierce competition when collaboration is low and disrespect for employees is pervasive, can create conditions where rules are broken to get ahead. Similarly, performance-oriented norms, such as the norms of being customer-oriented, detail-oriented, and results-oriented, can also increase the pressure to break rules by imposing unreasonable expectations and deadlines. Because each of the norms can be related to fraud to a varying degree, we combine them into a measure that is informative of fraud—fraud culture.

3. Data

For employee reviews, we use data provided by Glassdoor from 2008–2017. Glassdoor is one of the most widely used company review websites with millions of unique monthly visitors.[3] Reviews are anonymous, and companies cannot ask Glassdoor to take down negative reviews.[4] Reviewers self-certify their current or former employment with the company and provide their reviews under the give-to-get policy. Although there are many firms and millions of reviews, review coverage for some firms is sparse. To deal with sparsity, we aggregate all review data to a firm-year level. We require aggregated pros and cons to have at least 100 words coming from at least five reviews.

For fraud data, we use securities class action lawsuits collected by the Securities Class

[3] https://www.glassdoor.com/about/

[4] https://help.glassdoor.com/s/article/I-m-an-employer-What-can-I-do-about-negative-reviews-on-Glassdoor? Both reviews and company responses to reviews are moderated by Glassdoor. Glassdoor removes reviews when their policy of "one review, per company worked at, per year" is violated.

Action Clearinghouse at Stanford Law School, which collects all securities class action lawsuits in collaboration with Cornerstone Research. We use lawsuits with Rule 10b-5 claims or Section 11 fraud allegations. Rule 10b-5 covers fraud in connection with the purchase or sale of securities, e.g, untrue statements of material facts or acts to defraud. Section 11 covers misrepresentation or omission of material information in the securities registration statements. Securities class action lawsuits cover a wide set of issues compared to commonly studied, but infrequent, AAERs or financial statement restatements related to accounting misrepresentations. In addition to accounting issues, securities class action lawsuits cover misrepresentations in financial documents, false forward-looking statements, insider trading, and internal control weaknesses. These lawsuits specify a class period, that is, an alleged period over which a violation of the U.S. securities laws occurred. As a fraud event, we use a firm-year that overlaps with the class period, which may not necessarily coincide with the year when the lawsuit was filed. As a result, when we predict these events using employee reviews, the discussion is unlikely to be triggered by the lawsuit being filed. By doing so, we attempt to avoid review discussion being affected by the external events related to fraud detection and capture culture norms at the time of the violation.

The wider set of issues covered by securities class action lawsuits increases frequency of fraud events in our sample compared to accounting misrepresentations, which provides our prediction models with more data to learn from. We also consider three sets of fraud outcomes: *All fraud*, *Fraud*, and *Severe fraud*. The *All fraud* outcome captures all fraud allegations, even if the case was later dismissed. The *Fraud* outcome drops cases that were later dismissed. The *Severe fraud* outcome is restricted to the *Fraud* lawsuits with the settlement amount, if available, exceeding three million. These criteria were used before to identify cases where wrongdoing is more likely to occur (Dyck et al., 2010, 2023).

Table 1 presents descriptive statistics. The sample includes 11,399 firm-years for 2,278 firms. The frequency of securities class action lawsuits varies from 3.9% for *All fraud filings* to 1.5% for *Severe fraud filings*. For fraud outcomes defined based on a fiscal year overlapping with the class period, the frequency increases to 9.28% for *All fraud* and 3.59% for *Severe fraud*. That is, the average length of the class period is 2–3 years. The firms in the sample are relatively large with *Log sales* at 7.68 and profitable with *Return on assets* at 6.04%.

4. Fraud culture measure

4.1 Culture norms

We measure eight culture norms from pros and cons of employee reviews. These norms are adaptability, community, customer-oriented, detail-oriented, integrity, openness, results-oriented, and teamwork. Prior literature defines these norms using words or phrases associated with them. We collect all the words and phrases used to describe these norms from O'Reilly et al. (2014), Guiso et al. (2015b), Graham et al. (2016), Graham et al. (2022), and Li et al. (2021) and filter them through the corpus of pros and cons sentences. The idea of filtering is similar to Grennan (2019), who use WordNet to add related words and phrases to compile master texts for attributes of culture, and Li et al. (2021), who use word embeddings from `word2vec` (Mikolov et al., 2013a,b,c) to filter words based on meaning in the corpus of earnings conference calls. These word embeddings are computed by a neural network that learns low-dimensional vectors from review sentences that can be thought of as a representation of the meaning of words as used in reviews.

We train our `word2vec` embeddings on the corpus of pros and cons separately because the usage of words can differ with the polarity of the review.[5] After training two `word2vec` models, one for pros and another one for cons, we search for the words from the original lists to verify that their usage in reviews captures a specific cultural norm and to add related words for the same norm. These filtered words represent our set of seed words. In addition to the word itself, we also utilize its part-of-speech tag, e.g., adjective, noun, or verb, because the meaning of the word can change with its part-of-speech tag as well. For each cultural norm, we have two lists of seed words that correspond to pros and cons. This gives us 16 culture dimensions with two to 11 words in the corresponding seed words lists.

Having a set of seed words, we apply Cong et al. (2019) approach to constructing textual factors around these seed words. This approach creates clusters around seed words using agglomerative clustering, its nearest neighbor version, in the space of word embeddings. We remove stopwords as defined by the standard Python list when we construct clusters. At each iteration, the closest word is added with the cluster centroid recomputed at each step. This approach differs from Li et al. (2021), who select the closest 500 words to the centroid of the seed words, i.e., the average of word embeddings of their conference-calls-specific seed words list. As our main specification, we use clusters with 25 words; but clusters with seed words only, 50, and 100 words deliver similar, albeit slightly worse,

[5] The `word2vec` embeddings are trained on the sentence level. We use all words that are used more than five times in a specific corpus, and thus the stopwords are kept in training.

prediction accuracy for fraud. We noticed that the cluster quality starts to deteriorate at about 150 words, i.e., the cluster starts to incorporate words and phrases with ambiguous relevance to culture norms.

Figure 1 shows word clouds of clusters we constructed. Because we use relatively small clusters, we do not perform manual cleaning done by Li et al. (2021) for their 500-word dictionary. To compute culture norm exposure for each firm-year observation, we count the words in the corresponding cluster with each word being weighted equally. This approach results in sparse culture-norm vectors with each element corresponding to the word count in the corresponding cluster. We further normalize the length of culture-norm vectors to one according to the L2-norm. For normalization, we also add a dummy cluster that absorbs all the words falling outside of any cluster, so that for firm-years not containing any culture-norm words the normalized culture-norm vector stays a vector of zeros. That is, our culture measure captures the *relative* importance of different culture norms at firm-year level.

Figure 4 shows a heatmap for the correlation of culture measures. Overall, the correlation between different culture norms is quite low. Low correlation is consistent with how culture is quantified in prior literature, which is sometimes done using principal components analyses of value statements or culture attributes that attempt to identify orthogonal culture dimensions (e.g., O'Reilly et al., 1991, 2014; Grennan, 2019). One can thus think about each culture norm as a distinct dimension of culture that cannot be simply subsumed by other dimensions. Indeed, the highest positive correlation is between *Detail–oriented, pros* and *Results–oriented, pros* stands at 0.21, whereas the lowest negative correlation is between *Customer–oriented, pros* and *Results–oriented, pros* stands at −0.09. For cons dimensions, these correlations are weaker. For pros versus cons dimensions, these correlations are close to zero for the same norm. That is, there is no evidence that the same norm is discussed both as pros and cons at the same time.

4.2 Fraud culture measure development

We use gradient boosting of regression trees (Freund and Schapire, 1997; Friedman, 2001) to create fraud culture measure.[6] Fraud culture measure is the prediction computed from the culture-norm-based model with the best out-of-sample fit for fraud. Boosting methods combine many relatively inaccurate models such as regression trees to produce remarkable out-of-sample predictive performance (Schapire and Freund, 2012). A regression tree partitions the feature space into a set of regions with a different prediction in each partition. This approach searches for a target function in the function space and provides a consistent estimate for this function when boosting is stopped early (Jiang, 2004; Zhang and Yu, 2005; Bartlett and Traskin, 2007). Trees are fast to construct, interpretable, invariant to strictly monotone transformations of features, and immune to the effects of outliers in features and to the inclusion of irrelevant predictor features (Hastie et al., 2009, section 10.7). Each iteration adds a new tree that maximally improves the fit to the data given the already existing model producing a weighted sum of trees (Friedman, 2001). We use AdaBoost exponential loss function because our outcome is an indicator variable for fraud.

The algorithm depends on three meta-parameters: interaction depth of the regression trees,[7] the shrinkage or learning rate, the number of trees in the model. We set the shrinkage

[6] We use gradient boosting of regression trees as implemented in the `gbm3` R package by Ridgeway (2020).

[7] A value of 1 implies an additive model, a value of 2 implies a model with up to two-way interactions, etc. We consider values of 1, 2, 3, 5, and 7.

parameter to 0.01, which James et al. (2013, p. 323) identifies as a "typical value." There is a trade-off between shrinkage and the optimal number of trees in the model with smaller shrinkage requiring larger number of trees. We set the maximum number of trees to 3,000. Because the algorithm starts with a single tree and grows the model one tree at a time, this means we fit 3,000 trees with various interaction depths. Two parameters—the interaction depth of the regression trees and the number of trees—are chosen by cross-validation.

We perform cross-validation in the training data. Because fraud is rare, for each cross-validation partition, we balance our folds across firms, i.e., different firms are in different folds, and stratify based on the number of reviews, firm size, and *All fraud*. Each of the 20 cross-validation partitions has 5 folds, which corresponds to 100 folds in total. As a result, we have the average validation errors across 100 folds for each combination of the interaction depth and the number of trees in the model. We then choose the simplest model with an average validation error within 0.001 of the smallest average validation error achieved by models with various numbers of tress and interaction depths. This process favors simpler models with a smaller number of trees and lower interaction depths (e.g., Hastie et al., 2009; Kuhn and Johnson, 2013).

We perform train-test split on the firm level. We assign 70% of firms to the training set and the remaining 30% to the test set. When doing so, we make sure these firms are similar in terms of total number of reviews, number of reviews in a fiscal year, market value, total assets, sales, book-to-market, profitability, leverage, frequency of accounting restatements, and determinants of accounting restatements from Dechow et al. (2011) such as accruals, soft assets, growth in receivables, growth in inventories, growth in cash sales, growth in profitability, and equity issuance. The `word2vec` training, culture-norm clusters, and models for fraud prediction are all developed using the training set *only*. Once this is done, we compute culture-norm clusters and the corresponding fraud prediction scores on the test set to obtain the out-of-sample prediction accuracy.

We compare culture-norm-based models of fraud with an uninformed baseline and financial-variables models that include size, growth, and profitability. All variables are measured contemporaneously with fraud. An uninformed baseline uses frequency of fraud on the training data as its prediction for all firm-year observations in the test set. In Table 2, for all fraud outcomes, we find that culture-norm-based models outperform uninformed baseline and financial-variables-only models. When culture norms are added to the financial-variables-only models, the combined models outperform financial-variables only models. That is, culture norms are informative about fraud.

We refer to the prediction from the culture-norms-based model as "fraud culture." Table 3 presents descriptive statistics for the fraud culture measure. As expected, the average of fraud culture maps to the frequency of fraud outcomes in Table 1, because fraud culture measure is essentially the probability of fraud based on culture norms.

Table 4 shows in-sample linear probability regressions of fraud outcomes on fraud culture, firm size, growth, and profitability. For all fraud outcomes, our measures of fraud culture are positively associated with fraud even in the presence of financial variables. For financial variables, *Return on assets* is robustly negatively associated with fraud, that is, fraud is more likely when firms are performing poorly.

4.3 Individual dimensions of fraud culture

Figure 2 shows culture norms that matter most for predicting fraud. We compute the relative importance of various predictors as the reduction of the error attributable to this predictor as described in Friedman (2001). Fraud culture mostly varies with openness, adaptability, and the extent to which culture is customer- and detail-oriented.

The most important culture variables align with how the literature discusses culture norms in the context of fraud. Openness facilitates communication and transparency, which makes fraud both more visible and reportable. Adaptability captures organizational structure, that is, the extent to which organization is flexible and dynamic versus inflexible with a clear line of authority. Adaptability can have similar effect as openness by facilitating communication but can also capture politics and power in the organization. Clear rigid hierarchy can make it difficult to question those in power. For instance, Dallas (2003) writes that in Enron "Employees reported that what resulted was a 'yes-man' culture in which it became very important to be in the 'in-group."' Customer- and detail-oriented culture norms can impose unrealistic expectations for customer care and quality. This unwarranted pressure on employees can encourage breaking the rules.

Table 5 shows linear regressions of fraud culture measures on culture norms. For openness, *Openness, cons* is positively associated with fraud culture and *Openness, pros* is negatively associated with fraud culture. That is, firms with more open cultures that facilitate communication and information sharing are less likely to have fraud. For adaptability, both pros and cons being discussed in the reviews is associated with fraud culture. While adaptability captures aspects related to openness, it also captures organizational structure, such as flexibility (pros) versus authority (cons), and both are shown to be associated with fraud. For customer-oriented culture, *Customer-oriented, cons* is positively associated with fraud culture and *Customer-oriented, pros* is negatively associated with fraud culture. Customer-oriented culture captures the extent to which firms emphasise quality (pros) versus having issues and customer complaints (cons). When firms have greater quality issues and customer complaints, their fraud culture is also higher. For detail-oriented culture, *Detail-oriented, cons* is negatively associated with fraud culture and *Detail-oriented, pros* is positively associated with fraud culture. Detail-oriented culture captures the extent to which firms focus on design (pros) versus inattentive and careless (cons). Focusing on details and technology may exert pressure to perform, and thus make fraud more likely. Finally, integrity culture has received a lot of attention in the literature but did not come out as the most important predictor of fraud. Nevertheless, we find *Integrity, cons* is robustly positively associated with fraud culture, that is, unethical behavior facilitates fraud.

4.4 Variation in fraud culture

Figure 3 shows the average of fraud culture measure changing little over time with a small temporary drop coinciding with the Dodd-Frank Act, although these changes are larger for the median. The Dodd-Frank Act was enacted in 2010 and implemented a number of governance and whistleblower provisions that can affect fraud occurrence such as clawbacks on incentive compensation, independence of compensation committees, and whistleblower incentives and protection. It is unclear though whether this deep also represents a post-financial crisis reversal. Nevertheless, this deep is clearly temporary with fraud culture starting to trend back after 2014. So, even if there was a heightened attention to culture after the financial crisis (Lo, 2016), the effect of this attention seems to reverse later on. Fraud culture has also a relatively high temporal correlation between t and $t-1$ values, i.e., 0.57 for *Fraud*, 0.66 for *All fraud*, and 0.41 for *Severe fraud*.

Figure 5 shows industry distribution of fraud culture and individual culture norms. We consider 12 Fama-French industries. For each industry, we compute its relative deviation from the global average, i.e., relative percentage deviation of the average in the industry from the global average across all firms. Health care scores the highest on fraud culture. Indeed, securities litigation is the highest in health care (Cornerstone Research, 2024). Dyck et al. (2010) also find that monetary incentives for fraud reporting are the highest in health care because of government's procurement contracts, which results in 41% of frauds being reported by employees. Telecommunications and manufacturing have the next highest fraud culture. They also have a relatively high incidence of securities litigation. The lowest fraud culture is in retail, chemicals, and consumer durables. As for individual culture norms, health care has one of the lowest scores on *Customer-oriented, pros*, i.e., not really being customer-oriented, and one of the highest scores on *Integrity, cons* and *Openness, cons*, i.e., having low integrity and openness, which is consistent with its highest fraud culture. Whereas retail has the highest score on both *Customer-oriented, pros* and *Detail-oriented, cons*, i.e., being highly customer-oriented but less detail-oriented, but also the lowest scores on *Detail-oriented, pros*, *Adaptability, cons*, and *Openness, cons*, i.e., being not as low on adaptability and openness, which is consistent with its lowest fraud culture.

5. Fraud culture and CEO turnover

Corporate culture is viewed as relatively stable and enduring (Chatman and O'Reilly, 2016), and thus not easy to change. At the same time, because culture is a consensus about norms, an individual's behavior can shape these norms, especially when the individual is prominent in an organization and serves in a leadership role. As such, leaders can change culture. As O'Reilly et al. (2014), p. 599 suggest "[...] an organization's senior leaders, because of their salience, responsibility, authority, and presumed status, have a disproportionate impact on culture and may be a significant source of cultural influence." We test for the possibility of leaders to change fraud culture by looking at CEO turnover.

We collect data on CEO turnover from Equilar, which covers a near universe of public firms in the U.S. The idea is that CEOs are culture carriers. They can carry culture from one firm to another, thereby shaping culture in the new firm they join. We test for two possibilities. One possibility is that there could be matching by culture, including fraud culture, which means CEOs join firms with the culture that is similar to their previous firm. We test for this possibility by comparing culture in the firm before the incoming CEO joins to the culture of the incoming CEO, i.e., the culture of his previous firm. Another possibility is that the incoming CEO as a carrier of culture of the previous firm brings this culture to the new firm he joins, i.e., culture convergence.

Figure 6 presents results for matching and Figure 7 presents results for culture convergence. The samples are small because at least two years of CEO tenure are required to compute the average of fraud culture over CEOs' tenures and the transition years are dropped. Although the results are marginally statistically significant based on the sample of 30 CEOs, there is evidence for matching in Figure 6. There is a positive relation between the culture of the incoming CEO and the culture of the firm before the CEO joins the firm. This matching also translates to convergence in Figure 7. The sample is even smaller here because, for this test, we require at least two years in the previous firm and at least two years (excluding transition year) in the new firm after the incoming CEO joins the new firm. Again, the slope is positive but not statistically significant for the sample of 19 CEOs. That is, CEOs tend to join firms with similar fraud culture as in their previous firms and this culture tends to persist after they join.

One possibility explaining matching and convergence results is CEOs transitioning in the same industry and culture varying by industry. Indeed, Figure 8 shows that CEOs tend to stay in the same 12 Fama-French industry. Therefore, CEOs staying in the same industry in the pool of firms with similar culture mutes the possibility of culture change with CEO turnover.

6. Conclusion

Corporate culture is believed to matter for consequential firm outcomes including fraud. This paper leverages employee reviews from Glassdoor in developing measures of culture norms commonly studied in the literature. These culture norms are combined into a fraud culture measure to capture fraud related to securities class action lawsuits in the most predictive way. We find that the out-of-sample predictive ability of culture norms exceeds that of financial variables such as size, growth, and profitability. Fraud culture is stable over time, varies between industries, and is hard to change. There is matching between

CEOs and firms on fraud culture, which we attribute to within-industry CEO transitions with firms in the same industry having similar culture.

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Figure 1: **Culture norms**

Word clouds are for culture norms computed using pros and cons from Glassdoor reviews. For each culture norm, pros are on the top and cons are on the bottom. Size of the word is proportional to the inverse document frequency and to the closeness to the center of the cluster, and inversely proportional to the length of the word.

(a) Adaptability (b) Community (c) Customer-oriented culture (d) Detail-oriented culture

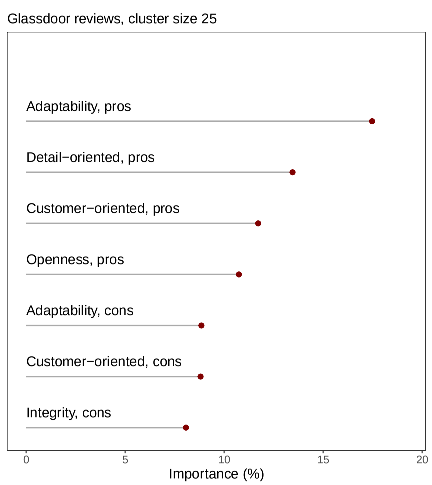
Figure 1: —*Continued*

(e) Integrity (f) Openness (g) Results-oriented culture (h) Teamwork

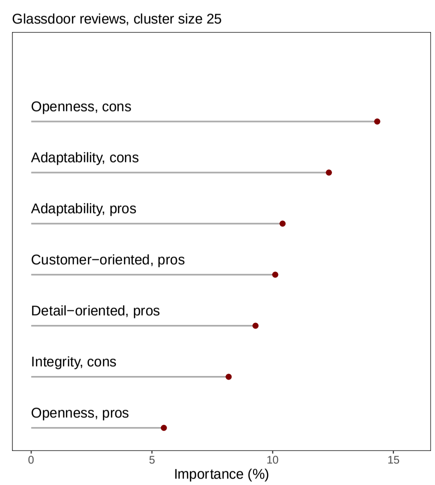
Figure 2: **Variable importance**

This figure depicts the relative importance of the top culture norms for predicting fraud. For each norm, importance is computed as the reduction of the error attributable to this characteristic as described in Friedman (2001).

(a) Fraud



(b) All fraud



(c) Severe fraud

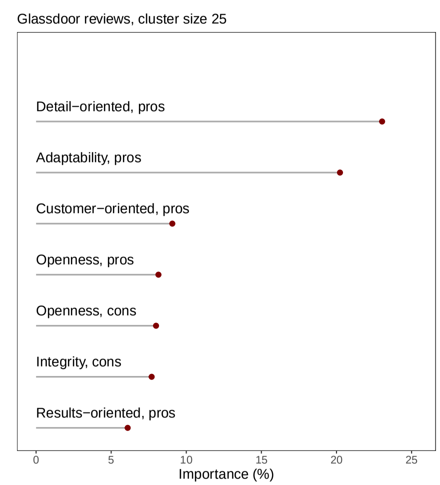


Figure 3: **Fraud culture by year**

This figure depicts fraud culture by fiscal year. The bottom and top lines are the 5th and 95th percentiles, and the middle solid line is the average value. The dotted line is the frequency of the actual fraud.

(a) Fraud

(b) All fraud

(c) Severe fraud

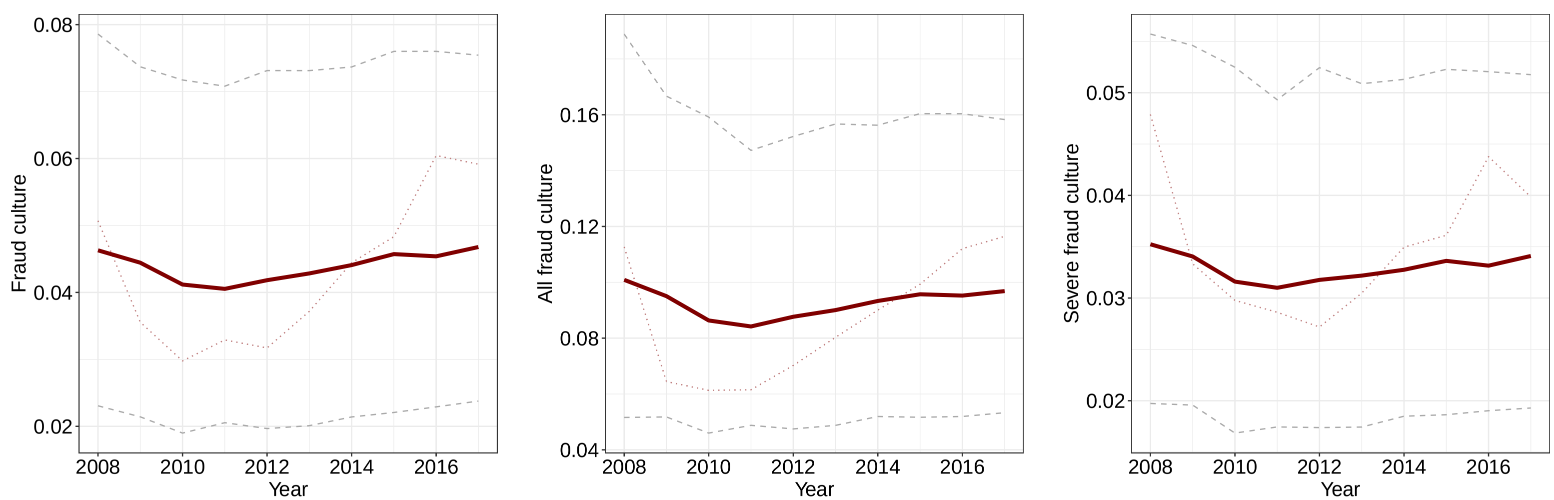
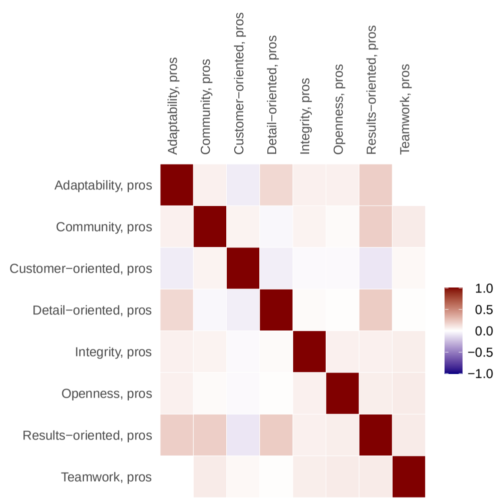


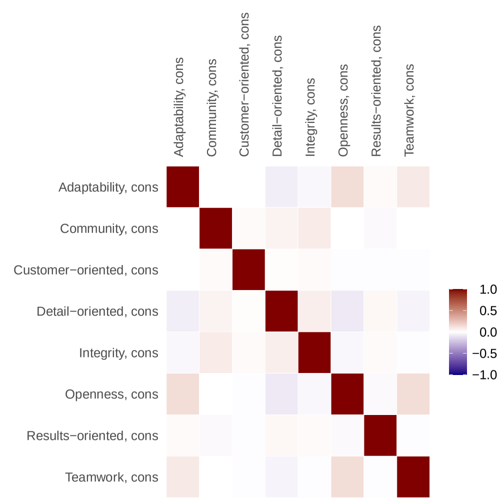
Figure 4: **Culture norms correlations**

This figure shows correlations between individual culture norms.

(a) Pros



(b) Cons



(c) Pros versus cons

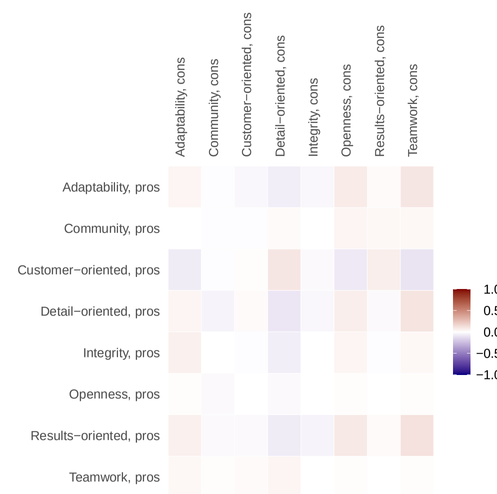


Figure 5: **Fraud culture and culture norms by industry**

For each of the 12 Fama-French industries, this figure shows relative deviations from the global average, i.e., relative percentage deviation of the average in the industry from the global average across all firms, for fraud culture and culture norms. *NoDur* is consumer nondurables such as food, textiles, and apparel. *Durbl* is consumer durables such as cars, furniture, and appliances. *Manuf* is manufacturing such as machinery, planes, and paper. *Enrgy* is oil, gas, and coal extraction and products. *Chems* is chemicals and allied products. *BusEq* is business equipment such as computers, software, and electronic equipment. *Telcm* is telephone and television transmission. *Utils* is utilities. *Shops* is wholesale, retail, and some services. *Hlth* is healthcare, medical equipment, and drugs. *Money* is finance. *Other* is other such as mines, construction, transportation, and business services.

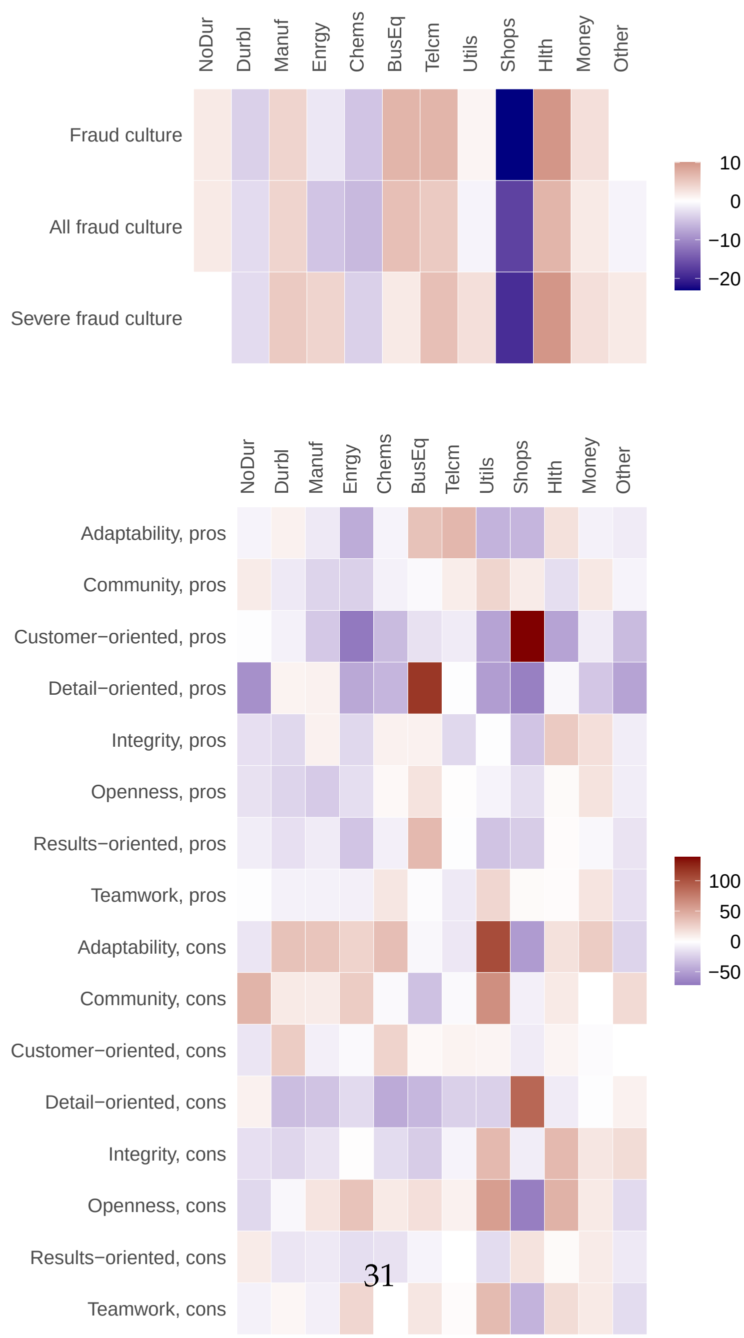


Figure 6: **Fraud culture matching**

This figure plots a linear regression for the culture of the incoming CEO as projected on the culture before the incoming CEO joins. At least two years of CEO tenure are required to compute the average of fraud culture over CEOs' tenures and the transition years are dropped. Both culture measures are standardized.

(a) Fraud (b) All fraud (c) Severe fraud

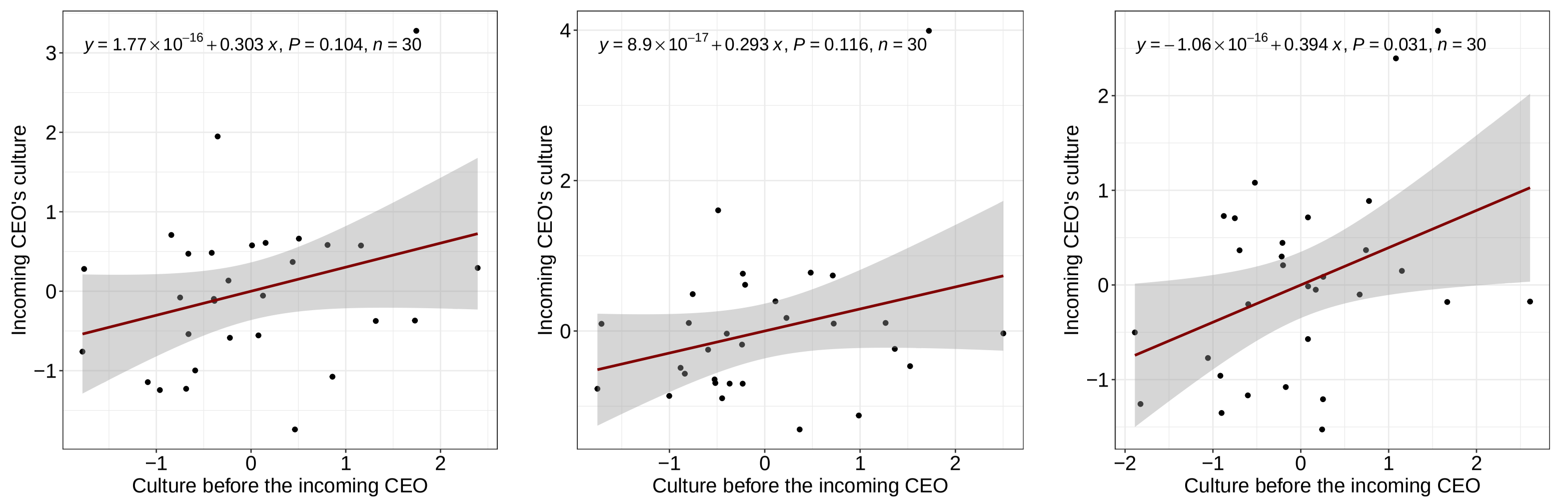
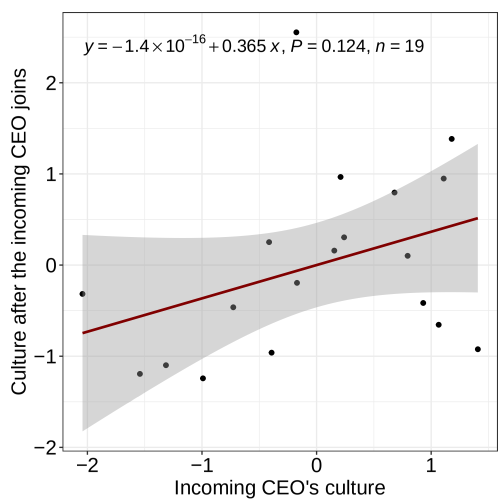


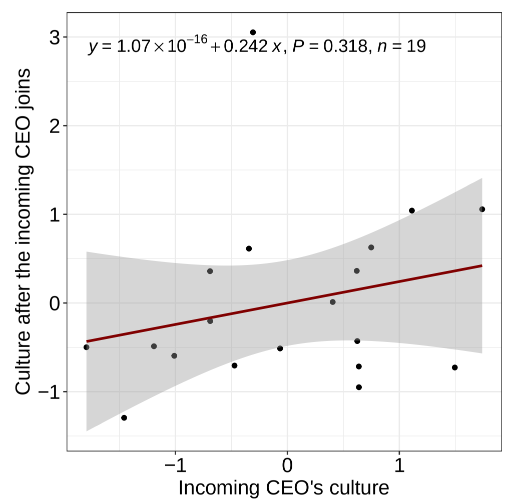
Figure 7: **Fraud culture convergence**

This figure plots a linear regression for the culture after the incoming CEO joins as projected on the culture of the incoming CEO. At least two years of CEO tenure are required to compute the average of fraud culture over CEOs' tenures and the transition years are dropped. Both culture measures are standardized.

(a) Fraud



(b) All fraud



(c) Severe fraud

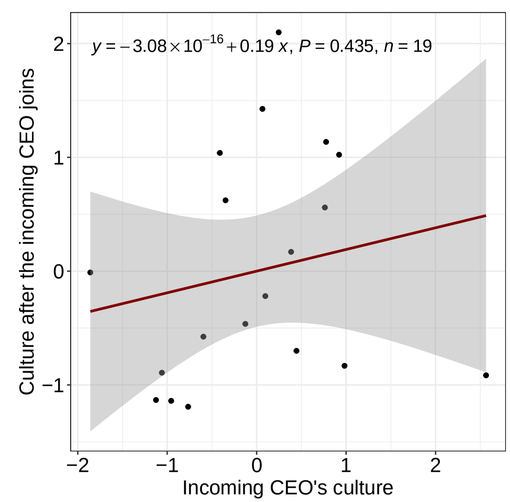


Figure 8: **CEO transitions by industry**

This figure depicts CEO transitions by industry. Size of the dot is proportional to the number of CEOs who moved between firms in the corresponding industries.

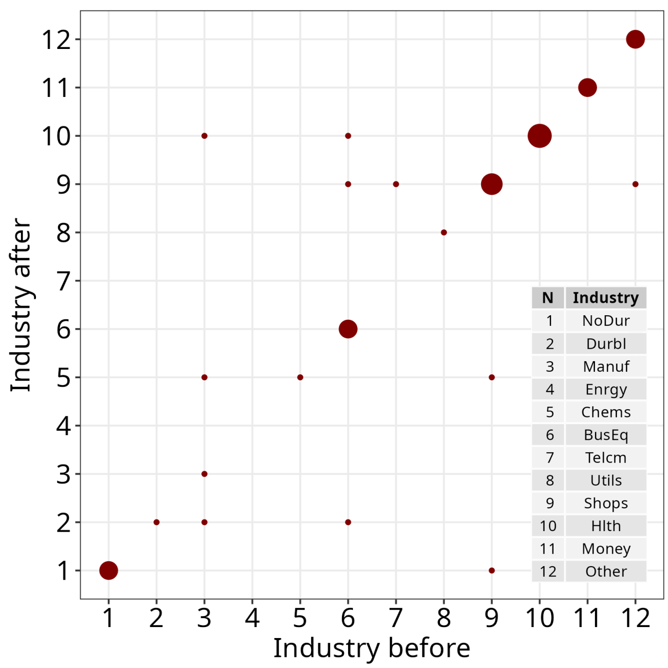


Table 1: **Descriptive statistics**

This table presents descriptive statistics. Fraud outcomes are set to one if a fiscal year overlaps with the class period of a security class action lawsuit. Lawsuit filings are security class action lawsuits. Financial variables are winsorized at 1- and 99- percentiles.

Panel A. Outcomes

Variable	Obs.	Mean	SD	Q5	Q25	Median	Q75	Q95
Fraud	11,399	0.0464	0.2104	0.0000	0.0000	0.0000	0.0000	0.0000
All fraud	11,399	0.0928	0.2902	0.0000	0.0000	0.0000	0.0000	1.0000
Severe fraud	11,399	0.0359	0.1860	0.0000	0.0000	0.0000	0.0000	0.0000

Panel B. Lawsuit filings

Variable	Obs.	Mean	SD	Q5	Q25	Median	Q75	Q95
Fraud lawsuit	11,399	0.0174	0.1307	0.0000	0.0000	0.0000	0.0000	0.0000
All fraud lawsuit	11,399	0.0390	0.1935	0.0000	0.0000	0.0000	0.0000	0.0000
Severe fraud lawsuit	11,399	0.0150	0.1216	0.0000	0.0000	0.0000	0.0000	0.0000

Panel C. Culture norms

Variable	Obs.	Mean	SD	Q5	Q25	Median	Q75	Q95
Adaptability, pros	11,399	0.0027	0.0037	0.0000	0.0000	0.0016	0.0042	0.0097
Community, pros	11,399	0.0033	0.0036	0.0000	0.0000	0.0026	0.0049	0.0099
Customer-oriented, pros	11,399	0.0030	0.0046	0.0000	0.0000	0.0012	0.0042	0.0121
Detail-oriented, pros	11,399	0.0023	0.0041	0.0000	0.0000	0.0000	0.0031	0.0100
Integrity, pros	11,399	0.0019	0.0029	0.0000	0.0000	0.0009	0.0027	0.0073
Openness, pros	11,399	0.0015	0.0026	0.0000	0.0000	0.0000	0.0020	0.0065
Results-oriented, pros	11,399	0.0077	0.0066	0.0000	0.0033	0.0064	0.0107	0.0200
Teamwork, pros	11,399	0.0070	0.0061	0.0000	0.0031	0.0060	0.0094	0.0182
Adaptability, cons	11,399	0.0007	0.0015	0.0000	0.0000	0.0000	0.0008	0.0033
Community, cons	11,399	0.0004	0.0013	0.0000	0.0000	0.0000	0.0001	0.0019
Customer-oriented, cons	11,399	0.0011	0.0018	0.0000	0.0000	0.0000	0.0014	0.0043
Detail-oriented, cons	11,399	0.0011	0.0020	0.0000	0.0000	0.0000	0.0014	0.0049
Integrity, cons	11,399	0.0007	0.0016	0.0000	0.0000	0.0000	0.0009	0.0034
Openness, cons	11,399	0.0006	0.0014	0.0000	0.0000	0.0000	0.0006	0.0030
Results-oriented, cons	11,399	0.0035	0.0037	0.0000	0.0004	0.0030	0.0050	0.0099
Teamwork, cons	11,399	0.0028	0.0034	0.0000	0.0000	0.0018	0.0040	0.0091

Panel D. Financial variables

Variable	Obs.	Mean	SD	Q5	Q25	Median	Q75	Q95
Size	11,325	7.6814	1.8057	4.6802	6.4485	7.6796	8.9391	10.7258
Book-to-market	10,927	0.4813	0.3975	0.0000	0.2079	0.3915	0.6520	1.2198
Return on assets	11,325	0.0604	0.1259	-0.1518	0.0228	0.0668	0.1180	0.2360

Table 2: **Out-of-sample test results**

This table presents out-of-sample test results. We compute the test error as `ln(1 + AdaBoost error)`. By construction, these errors are positive with lower values corresponding to better accuracy.

Outcome	Mean losses				
	Uninformed		Reviews		Firm
Fraud	0.346	$>^{***}$	0.337	$<^{***}$	0.347
All fraud	0.440	$>^{***}$	0.429	$<^{***}$	0.437
Severe fraud	0.321	$>^{***}$	0.315	$<^{**}$	0.323

Table 3: **Descriptive statistics for fraud culture**

This table presents descriptive statistics for fraud culture measures. Fraud culture is the prediction from the corresponding culture-norms-based models.

Variable	Obs.	Mean	SD	Q5	Q25	Median	Q75	Q95
Fraud culture	11,399	0.0444	0.0164	0.0214	0.0317	0.0416	0.0552	0.0747
All fraud culture	11,399	0.0931	0.0352	0.0505	0.0662	0.0855	0.1136	0.1582
Severe fraud culture	11,399	0.0330	0.0112	0.0183	0.0252	0.0310	0.0392	0.0521

Table 4: **Linear regressions of fraud on fraud culture and financial variables**

This table presents linear probability models that project fraud outcomes on fraud culture and financial variables. Standard errors are clustered by firm and year.

Panel A. Fraud

	(1)	(2)	(3)
Fraud culture	0.145***		0.143***
	(0.016)		(0.014)
Size		0.080***	0.022
		(0.022)	(0.019)
Book-to-market		0.016	0.035**
		(0.016)	(0.016)
Return on assets		−0.071***	−0.048***
		(0.013)	(0.012)
R^2	0.021	0.007	0.025
Obs.	11,399	10,925	10,925

Panel B. All fraud

	(1)	(2)	(3)
All fraud culture	0.194***		0.189***
	(0.020)		(0.017)
Size		0.126***	0.032
		(0.029)	(0.022)
Book-to-market		0.005	0.033
		(0.020)	(0.021)
Return on assets		−0.098***	−0.067***
		(0.014)	(0.013)
R^2	0.037	0.015	0.043
Obs.	11,399	10,925	10,925

Panel C. Severe fraud

	(1)	(2)	(3)
Severe fraud culture	0.134***		0.133***
	(0.014)		(0.014)
Size		0.064***	0.023
		(0.018)	(0.017)
Book-to-market		0.037**	0.048***
		(0.015)	(0.015)
Return on assets		−0.049***	−0.030**
		(0.012)	(0.012)
R^2	0.018	0.006	0.022
Obs.	11,399	10,925	10,925

Table 5: **Linear regressions of fraud culture on culture norms**

This table presents linear regressions that project fraud culture on culture norms. Standard errors are clustered by firm and year.

Panel A. Fraud culture

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Adaptability, cons	0.248***								0.192***
	(0.017)								(0.015)
Adaptability, pros	0.319***								0.265***
	(0.013)								(0.010)
Community, cons		0.010							0.009
		(0.009)							(0.010)
Community, pros		−0.021							−0.015
		(0.017)							(0.009)
Customer-oriented, cons			0.069***						0.075***
			(0.009)						(0.007)
Customer-oriented, pros			−0.393***						−0.328***
			(0.015)						(0.014)
Detail-oriented, cons				−0.159***					−0.103***
				(0.010)					(0.007)
Detail-oriented, pros				0.200***					0.125***
				(0.015)					(0.011)
Integrity, cons					0.130***				0.152***
					(0.012)				(0.012)
Integrity, pros					0.048***				0.010
					(0.011)				(0.008)
Openness, cons						0.267***			0.179***
						(0.018)			(0.012)
Openness, pros						−0.041***			−0.060***
						(0.009)			(0.009)
Results-oriented, cons							0.055***		0.080***
							(0.015)		(0.012)
Results-oriented, pros							0.115***		−0.018*
							(0.018)		(0.010)
Teamwork, cons								0.169***	0.056***
								(0.015)	(0.011)
Teamwork, pros								−0.086***	−0.075***
								(0.010)	(0.011)
R^2	0.170	0.001	0.159	0.071	0.019	0.073	0.016	0.036	0.405
Obs.	11,399	11,399	11,399	11,399	11,399	11,399	11,399	11,399	11,399

Table 5: —*Continued*

Panel B. All fraud culture

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Adaptability, cons	0.259***								0.202***
	(0.020)								(0.018)
Adaptability, pros	0.209***								0.159***
	(0.017)								(0.015)
Community, cons		−0.003							−0.003
		(0.007)							(0.011)
Community, pros		−0.006							0.001
		(0.015)							(0.009)
Customer-oriented, cons			−0.006						−0.000
			(0.008)						(0.007)
Customer-oriented, pros			−0.284***						−0.225***
			(0.010)						(0.008)
Detail-oriented, cons				−0.109***					−0.054***
				(0.009)					(0.007)
Detail-oriented, pros				0.151***					0.095***
				(0.013)					(0.009)
Integrity, cons					0.094***				0.115***
					(0.009)				(0.010)
Integrity, pros					0.036***				0.010
					(0.010)				(0.009)
Openness, cons						0.344***			0.276***
						(0.023)			(0.018)
Openness, pros						−0.048***			−0.053***
						(0.009)			(0.008)
Results-oriented, cons							0.056***		0.075***
							(0.013)		(0.011)
Results-oriented, pros							0.084***		−0.016*
							(0.015)		(0.008)
Teamwork, cons								0.146***	0.042***
								(0.014)	(0.011)
Teamwork, pros								−0.151***	−0.146***
								(0.013)	(0.013)
R^2	0.115	0.000	0.081	0.038	0.010	0.120	0.010	0.043	0.314
Obs.	11,399	11,399	11,399	11,399	11,399	11,399	11,399	11,399	11,399

Table 5: —*Continued*

Panel C. Severe fraud culture

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Adaptability, cons	0.184***								0.137***
	(0.015)								(0.011)
Adaptability, pros	0.317***								0.289***
	(0.008)								(0.009)
Community, cons		0.011							0.004
		(0.010)							(0.010)
Community, pros		−0.135***							−0.090***
		(0.015)							(0.007)
Customer-oriented, cons			0.038***						0.036***
			(0.008)						(0.008)
Customer-oriented, pros			−0.371***						−0.313***
			(0.012)						(0.014)
Detail-oriented, cons				−0.068***					−0.022***
				(0.014)					(0.008)
Detail-oriented, pros				0.290***					0.248***
				(0.020)					(0.016)
Integrity, cons					0.188***				0.204***
					(0.017)				(0.016)
Integrity, pros					−0.016				−0.036***
					(0.010)				(0.009)
Openness, cons						0.282***			0.218***
						(0.021)			(0.015)
Openness, pros						−0.023*			−0.021**
						(0.013)			(0.010)
Results-oriented, cons							0.020		0.046***
							(0.019)		(0.013)
Results-oriented, pros							−0.056***		−0.193***
							(0.017)		(0.011)
Teamwork, cons								0.162***	0.063***
								(0.016)	(0.010)
Teamwork, pros								−0.148***	−0.120***
								(0.009)	(0.010)
R^2	0.140	0.018	0.139	0.092	0.036	0.080	0.004	0.047	0.466
Obs.	11,399	11,399	11,399	11,399	11,399	11,399	11,399	11,399	11,399