Video-Based Deception Detection and Financial Fraud

ABSTRACT

Using a comprehensive visual deception score estimated with computer vision and machine learning algorithms, we find that visual deception cues revealed from mandatorily disclosed IPO roadshow videos in China predict IPO financial fraud. The predictive power of visual cues is incremental to financial, textual, and audio fraud indicators. Analyses on these deception cues show that they are well grounded in prior psychology research. Furthermore, decomposing the entire video into five topics, we show that only the deception score of the topic on financial performance predicts fraud. We further show that insiders from the firms with higher visual deception scores are more likely to sell stocks quickly following the expiration of lockup periods and the subsequent stock returns of these firms are significantly lower. Our study highlights the potential benefits of mandatory video disclosure to investors and regulators.

Keywords: fraud, deception, video analyses, machine learning

JEL Codes: M41, G34

1. Introduction

"They (the movements of expression) reveal the thoughts and intentions of others more truly than do words, which may be falsified."

——*Charles Darwin (1872)*

Detecting financial fraud is of considerable interest to practitioners, regulators, and academics in accounting and finance. Researchers have used a variety of methods to detect fraud from building up accounting-based quantitative models (e.g., Dechow et al., 1996; Cecchini et al., 2010; Dechow et al., 2011) to using the styles and topics of financial reports or conference call transcripts (Larcker and Zakolyukina, 2012; Purda and Skillicorn, 2015; Brown et al., 2020). Despite extensive research on the subject, however, few studies examine the usefulness of non-text and nonverbal information in predicting fraud. This paper extends prior literature by studying the information content of visual cues.

Visual information may be particularly useful in detecting deception because facial movements are hard to control and may reveal people's unconscious behavior and true emotions (Darwin, 1872; Duchenne, 1990; Ekman, 2006; Schubert, 2006; Porter and Ten-Brinke, 2008). Darwin (1872, p.79) notes that certain facial actions that cannot be created voluntarily may nonetheless be involuntarily expressed in the presence of genuine emotion. When people lie, their faces often contain two messages—what they want to show and what they want to conceal. These hidden complicated emotions often leak in the form of a micro expression, a brief involuntary facial expression revealing true emotion (Ekman, 1985/2001; Ekman, 2009a). While a single micro expression does not offer conclusive proof of lying, continuous facial expression is the most important behavioral source in detecting deception (Ekman and Friesen, 1969; Ekman, 2009a). Based on these arguments in psychology, we examine whether the cues in IPO roadshow video reveal the likelihood of lying about IPO firm's financial performance. The prediction is not straightforward ex ante. IPO is a highly significant event for corporations, executives may extensively rehearse to control their facial muscles and conceal their emotions, which may result in visual cues having no predictive power for financial fraud.

One challenge to empirically examine the usefulness of visual cues in predicting financial fraud is to identify a setting in which video disclosure is mandatory. So far, the video disclosure studied in prior literature is voluntary (Blankespoor et al., 2017; Choudhury et al., 2019; Li et al., 2021; Dávila and Guasch, 2022; Banker et al., 2023; Hu and Ma, 2023). Voluntarily provided videos may, however, have limited power in predicting fraud due to selection bias, because the fraudulent firms may choose not to provide videos. [1] To overcome this challenge, we take advantage of the IPO roadshow videos in China, which are required to be provided by all Chinese IPOs.

Specifically, one day before the public offering, all IPO firms in China are required to live stream managers presenting the roadshow in video format online to the public. This roadshow is typically attended by the board chairman, the board secretary, the CEO, and the CFO. The videos are available for download once the roadshows are over. We use a web crawler to download all roadshow videos of companies listed on the Shenzhen Stock Exchanges (SZSE) from January 1, 2014, to December 31, 2022, from Quanjing, an exchange-affiliated online platform. We start with 1,269 firms and retain a final sample of 1,138 firms after removing problematic video recordings and requiring non-missing controls.

To construct a visual deception score to detect executive's deceptive behavior, we adopt

[1] The *video files* of the roadshow presentation are not mandatory in the U.S. IPO firms may file with the SEC or publicly disclose a bona fide electronic version of the roadshow presentation, but the electronic files are not required to be in video. In Blankespoor et al. (2017) that study IPO roadshows in the U.S., some sample IPO firms provide only audio roadshow files. We confirmed that firms' roadshow presentation files in the U.S. can be in audio instead of video by collecting a sample of IPO roadshows from July 30, 2021 to December 17, 2021 hosted on RetailRoadshow.com website.

machine learning techniques that are known for the capabilities of working with high-dimensional features of facial movements. Micro-expressions with less than 0.25 second can be difficult for human eyes to recognize (Ekman, 1985/2001; Yan et al., 2018), yet machines can view videos frame by frame at any density. We follow the four steps in prior automated deception detection research to estimate our score (Pérez-Rosas et al., 2015; Morales et al., 2017; Wu et al., 2018), including video parsing, feature extraction, model training, and deception score calculation. One concern regarding the use of machine learning algorithms in economic research is the opacity of the technology (Hu and Ma, 2023). We address this concern by adopting open-source packages (e.g., Face++, OpenFace) to extract features, and using a publicly available training dataset (i.e., The Real-life Trial dataset, hereafter RLT dataset) to train the deception detection machine learning models. As a result, our approach enables high replicability and transparency.

After creating the visual deception score, we proceed to investigate whether IPO firms with higher scores are more likely to have committed financial fraud. We identify financial fraud ex-post as the fraud related to accounting manipulation or misconduct, committed during the IPO process but revealed during the post-IPO period (referred to as IPO fraud hereafter). Our results reveal a significantly positive relationship between our visual deception score and the likelihood of IPO fraud controlling for existing financial-, textual-, and audio-based predictors. The results are economically significant. When the visual deception score increases from the first quartile to the third quartile, the mean probability of IPO fraud increases from 2.43 percent to 3.92 percent, which represents a 61.32 percent increase. In addition, the AUC of the model with visual deception score is significantly higher than the AUC of the model without it, indicating that adding the video-based information improves the performance of the prediction model.

One underlying mechanism of our results is that managers at IPO roadshows know about the misrepresentation of financial performance and the machine-based visual deception score captures the deception cues in their roadshow presentations. An alternative explanation is that the visual deception score is only capturing a manager-level characteristic related to their innate tendency to lie and deceive or a firm-level characteristic that is correlated with the deception score. To address this alternative explanation, we implement sentence-level analyses and show that our financial IPO fraud is only predicted by the visual deception scores during the discussions of financial results. The evidence indicates that our machine-generated deception score captures more nuanced information that goes beyond firm or manager characteristics. It may vary depending on the specific topics discussed within a manager's presentation, potentially revealing the nature of the fraud being committed, which is hardly achievable by firm or manager characteristics that will stay fixed for a given manager/firm.

We next examine the model input features carefully to gain better understanding of what our machine-learning-based deception score captures by building connections among three important elements — the existing psychology research on deception, the deception detection machine learning models trained using RLT data, and the fraud prediction in the IPO roadshow setting. We find a set of input visual features that are crucial for deception detection according to the existing psychology research are successfully picked up by our machine learning model trained in the RLT setting. In addition, the exact same set of features significantly predicts fraud in our IPO setting while other features fail to do so. The evidence suggests two important insights. First, our machine learning model indeed captures deception cues well-grounded in the psychology literature rather than random factors. Second, the deception features identified are useful across different contexts, cultures, and races, consistent with findings in previous psychology research (Ekman, 1973; Ekman, 1998; Ekman, 2003; Ekman, 2009b).

We check whether insider sales and stock returns show any abnormal patterns across the firms with different deception scores. We find that managers from the firms with higher deception scores have higher stock sales in the first month immediately after the lock-up period expires. The fact that these managers sell more shares immediately after they are allowed to do so is consistent with the conjecture that managers know that the reported financial performance of their firms are not sustainable. Indeed, we find firms with higher deception scores exhibit lower buy-and-hold abnormal returns during 60- or 120-day windows after the IPO lock-up period expires.

We implement various robust checks on our methods and results. First, we find that the deception score of the roadshow host is lower than that of firm managers and does not predict fraud, providing validity of our deception score measure. Second, our results are robust to excluding the video segments when individual speakers lower their heads during speeches, different ways of averaging managers' deception scores, excluding IPO-year fraud cases whose fraud periods are not known to be strictly before the IPO date. In addition, we find robust results to alternative machine learning classifiers (i.e., Gradient Boosting Decision Tree classifier and Multi-Layer Perceptron model), the use of transfer learning method to minimize the difference between the court trail setting and our IPO setting, different ways of controlling financial and text-based fraud indicators, and alternative models with different fixed effects and different ways to cluster standard errors. Finally, our results are robust to the exclusion of any single year, province, or industry from our sample, suggesting that small deviations in the sample composition are unlikely to significantly impact our results.

Our paper contributes to the literature on the applications of unstructured data. For the first time, we show that deception cues revealed from video disclosure can aid in the detection of financial misreporting. By developing a machine-based visual deception score, we offer a new tool to the existing approach of fraud detection, which primarily relies on financial information, textual features, and vocal cues (e.g., Dechow et al., 1996; Larcker and Zakolyukina, 2012; Hobson et al., 2012). Although recent studies start to examine information contained in images and videos, research using video information mainly focuses on forecasting firm fundamentals or funding outcomes, for which whether the video information is voluntarily or mandatorily disclosed is not critical (Blankespoor et al., 2017; Akansu et al., 2017; Choudhury et al., 2019; Li et al., 2021; Dávila and Guasch, 2022; Banker et al., 2023; Hu and Ma, 2023). Regarding fraud prediction, however, the sample selection bias associated with voluntary disclosure could be detrimental rendering the disclosed video information useless. We contribute to the literature by identifying a mandatory video disclosure setting and showing that the visual deception cues extracted are useful at predicting fraud. In computer science, Gong et al. (2019) use a sample of 286 videos to construct a negative emotion measure to predict fraud using IPO videos. Emotions are however conceptually different from deception cues. Grounding on prior psychology research, we examine how deception cues embedded in video motions predict frauds.[2] We empirically confirm that a common set of deception cues well-grounded in the psychology literature such as face and eye movements is not only weighted more heavily by our machine learning model trained in RLT setting but also significant predicts fraud in the IPO setting. By contrast, features like nose and chin movements that have very little support from the psychology literature are less important/significant in the trained model as well as in the IPO fraud prediction task. The evidence suggests that the visual deception cues well-grounded in psychology research are effective at detecting lies in financial contexts, consistent with certain deception cues being universal across contexts.

Our paper has important implications for regulators and practitioners. Regulators could consider developing and integrating machine-trained visual deception models into their toolbox in identifying red-flags for potential frauds. Investors should be informed that video information is useful in assessing the reliability of firms' reported financial performance.

[2] For completeness, we control for the visual-based negative emotion measure developed in Gong et al. (2019) in our analyses.

2. Background and literature review

2.1. Related literature in accounting and finance

There is a substantial body of accounting literature that explores fraud detection using various data and models. Early research has primarily focused on the usefulness of financial and non-financial information such as total accruals, F-Score index, and corporate governance features in detecting financial misreporting and assessing fraud risk (Bayley and Taylor, 2007; Dechow et al., 1996; Beasley, 1996; Farber, 2005; Dechow et al., 2011). Real production activity measures and customers' accounting information are also shown to be effective at predicting financial fraud (Allee et al., 2021; Li et al., 2023). In addition to innovations regarding model input, recent studies have proposed more sophisticated models than linear or logistic models to improve the fraud predicting performance. Cecchini et al. (2010) develop a new fraud prediction model using support vector machines (SVM) with a financial kernel and find this model outperforms traditional fraud prediction models. Perols et al. (2017) introduce and evaluate Multi-Subset Observation Undersampling (OU) and Multi-Subset Variable Undersampling (VU) methods to improve the quality of prior fraud prediction models.

Apart from financial and non-financial data, there is a growing body of accounting literature that examines the fraud predicting performance of unstructured data, such as textual (Larcker and Zakolyukina, 2012; Purda and Skillicorn, 2015; Horberg and Lewis, 2017; Brown et al., 2020; Campbell and Shang, 2021), picture (Jia et al., 2014; Ham et al., 2017), and audio information (Hobson et al., 2012). Little research has documented the usefulness of video information in predicting fraud. It is probably due to the inherent sample selection bias of voluntarily disclosed video data, i.e., fraudulent firms may avoid providing videos, or the challenges imposed by the previously available technology, i.e., to link the visual cues to psychology theories.

Voluntarily disclosed videos, however, have been processed for other purposes. Using entrepreneurs' roadshow videos and Amazon's Mechanical Turk, Blankespoor et al. (2017) develop a composite measure of investor perception and find a positive association between the overall perception of a firm's CEO and IPO firm valuation. Choudhury et al. (2019) analyze videos of interviews with "star CEOs from emerging markets" and identify five managerial communication styles and find that CEOs who express themselves dramatically are less likely to undertake mergers and acquisitions. Some researchers analyze early-stage firm entrepreneurs' pitch videos in crowdfunding platforms or investment forums and find that speech details (Li et al., 2021), facial expressions (Hu and Ma, 2023), and physical expansiveness (Dávila and Guasch, 2022) could impact funding outcomes. Banker et al. (2023) analyze CNBC's CEO interviews and find that the stock market reacts negatively to the CEO's dynamic hemifacial asymmetry of expressions.

Complementing both themes of literature and taking advantage of an empirical setting in which video disclosure is mandatory, we study whether the visual deception cues help reveal the likelihood of managers' lying of firms' financial performance.

2.2. Related literature in psychology

Deception detection is a critical area of psychology research. The foundation for using facial expressions as deception cues lies in the inhibition hypothesis, which was initially foreshadowed by Darwin's (1872) observations on the involuntary nature of facial expressions. Darwin suggests that muscles difficult to voluntarily control may elude efforts to suppress or conceal expressions, thereby revealing genuine emotions. This hypothesis is supported by neuroanatomy, which identifies two motor pathways controlling facial movement: the subcortical extrapyramidal motor system, responsible for spontaneous facial expressions of felt emotions, and the cortical pyramidal motor system, which controls voluntary facial expressions

(Brodal, 1981; Rinn, 1984). Genuinely felt emotion originates in the subcortical areas of the brain and is involuntarily propelled onto the face via the extrapyramidal motor system. In contrast, posed or faked expressions originate in the cortical motor strip and are voluntarily expressed in the face via the pyramidal motor system.[3] The implication of the inhibition hypothesis and its neuroanatomy foundation is that there are differences between genuine and faked expressions, providing a theoretical basis for visual deception cues. Psychology researchers, being inspired by the above findings in neuroanatomy literature, have proposed various theoretical approaches to predict nonverbal deception cues. These theories suggest that liars may experience stronger emotions, higher cognitive load, and may use more and different strategies to appear convincing (Vrij et al., 2010).

Both neuroanatomical foundations and psychology theories suggest that facial cues are useful for deception detection, and that there may exists a common set of features that are effective indicators of lies across different settings, as micro expressions and subtle facial cues associated with lies are largely uncontrollable and exhibit minimal variation across different culture, age, and gender (Ekman, 1973; Ekman, 1998; Ekman, 2003; Ekman, 2009b).[4]

Psychology researchers have since conducted experiments or field studies to identify specific deception cues by training raters to analyze videotapes or audiotapes of truth-tellers and liars. In laboratory studies, video footage and/or transcripts of participants who were instructed by researchers to tell the truth or lie for the purpose of the experiment are analyzed

[3] Research documenting these differences is sufficiently reliable to become the primary diagnostic criteria for certain brain lesions prior to modern imaging methods. For instance, patients with cortical motor strip lesions may struggle with voluntary facial control but retain spontaneous emotional expressions (Brodal, 1981). Conversely, lesions in the extrapyramidal motor system, such as in Parkinson's disease, result in a loss of spontaneous emotional expressions while retaining voluntary control (Rinn, 1984).

[4] The notion that certain deception cues are universal across cultures is also supported by evolutionary psychology. According to this theory, facial expressions of emotion are innate, inherited, and therefore universal. The university of facial expressions of emotion is one of Darwin's central themes in Darwin (1872). For support this insight, he gathered data himself, asking those who had lived or traveled in foreign countries about the expressions they had observed. Numerous subsequent research supports his proposal (e.g., Ekman, 1998; Scherer and Wallbott, 1994).

(Vrij et al., 2000; Vrij, 2006).[5] In real-life studies, typically called "field studies," video footage of real-life settings, such as court judgement, is analyzed (Porter and Ten Brinke, 2009).

Hundreds of facial cues are examined in the literature (DePaulo et al., 2003; Hartwig and Bond, 2014). The evidence collectively suggests that while no single cue is an indisputable predictor of deception, combinations of cues can significantly aid in deception detection (Ekman, 1985/2001; Vrij et al., 2010). Specifically, a common set of cues particularly useful for deception detection emerge from the extended line of research on deception under various contexts and lab environments, including cues from eye, brow, mouth, and face movements (Ekman and Friesen, 1982; Riggio and Friedman, 1983; Ekman, 1985/2001; Porter and Ten-Brinke, 2008).

2.3. Related literature in automated deception detection

Despite the identification of various deception cues, humans still have a limited ability to recognize lying, and their accuracy rates are not much better than random guessing (Ekman, 2009a). Computer science researchers have therefore been working on developing reliable and efficient systems to detect deceptive behavior and separate liars from truth-tellers using machine learning algorithms. Pérez-Rosas et al. (2015) create the first real-life deception detection video dataset (the Real-life Trial dataset) and present a multimodal system for detecting deception in real-life videos, using human coders to extract features from text, audio and visual dimensions. Their models achieve deception detection classification accuracies in the range of 60-75 percent. While competing on different techniques and machine learning classifiers, the common theme of the literature is the use of the Real-life Trial dataset (e.g., Abouelenien et al., 2014; Gogate et al., 2017; Wu et al., 2018; Ding et al., 2019). Overall, this

[5] In some studies, senders lied or told the truth about their beliefs or opinions or about personal facts. In others, senders looked at videotapes, films, slides, or pictures.

line of research uses various models to detect deception and find the importance of different modalities like visual, audio and text. For example, Gogate et al. (2017) incorporate audio cues for the first time along with the visual and textual cues in deception detection. Recently, researchers start to use computer vision algorithms (usually based on machine learning techniques) to identify expressions and movement from faces automatically instead of asking humans to manually code. Wu et al. (2018) show that their fully automated approach outperforms the state-of-the-art methods using human annotations of micro-expressions for deception detection by 5%. Morales et al. (2017) present an *open-source* multimodal feature extraction tool and find that multimodal features derived from the fully automated system can match the performance of a manually handcrafted feature set in deception detection. We follow Morales et al. (2017) and use a fully automated and open-sourced system to exact features for replicability and transparency.

3. Data

Regulation No.12 of 2001 issued by the China Securities Regulatory Commission (CSRC) requires firms to conduct roadshows which will be broadcasted over the internet one day prior to their initial offerings. These internet roadshows consist of three parts: an opening speech, a Q&A session, and an ending speech. During the opening and ending speeches, managers of the IPO firms present information about the firm's status and performance. Figure 1 provides several snapshots of Chinese IPO roadshow videos. These mandatory IPO online roadshows provide a unique setting to examine whether visual cues predict financial fraud.

3.1. Sample selection

Our sample is composed of Chinese companies that went public on the Shenzhen Stock

Exchange between January 1, 2014, and December 31, 2022.[6] We obtain IPO roadshow videos from the website Quanjing (https://rs.p5w.net), which posts presentation videos for public offerings.[7] We are unable to download 66 IPO roadshow videos by the time we implement the downloading procedures, and additional 29 firms' roadshow videos are excluded as they are damaged or cannot be analyzed. We further exclude 13 financial firms and 23 firms with missing data for control variables. As shown in Panel A of Table 1, our final sample comprises a total of 1,138 IPO videos. Panel B reports the summary statistics on the profiles of participants. We find that, on average, six participants show up and the board chairman participates in nearly all IPO roadshows (96%).

3.2. Financial fraud

Our dependent variable, *FRAUD*, is an indicator variable that captures the occurrence of financial fraud committed by a firm before or during the IPO year and revealed ex post. Financial fraud refers to instances where a firm intentionally deceives stakeholders (Karpoff et al., 2017). In the U.S. setting, previous research uses enforcement actions involving accounting and auditing issues (AAERs) published by the SEC (e.g., Dechow et al., 2011). Following this approach, we compile a dataset to capture the AAER-type fraud in China by using data provided by the China Stock Market and Accounting Research (CSMAR).

Specifically, a company is considered to have committed fraud if it receives a sanction from the Chinese Security Regulatory Committee (CSRC) or the exchanges for misbehavior.[8]

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[6] We start the sample in 2014 to avoid the mandatory IPO suspension and the overhaul of the IPO disclosure and pricing regulations by the CSRC in 2013. Our sample ends in 2022 to ensure that we have one year for fraud to be detected following the IPOs by the time we collect the data. Our results are robust to ending the sample in 2019 to leave more time for the fraud to be discovered (untabulated).

[7] The platform hosting the online roadshows of all IPOs listed on the Shenzhen Stock Exchange provides a teleprompter for speakers to ensure that their faces and eye areas are fully visible. The Shanghai Stock Exchange also has a similar IPO roadshow video disclosure requirement. We excluded the roadshows of firms listed on the Shanghai Stock Exchange from our analysis as the exchange does not provide the teleprompter service and the presenters tend to lower their heads to read transcripts, making facial analysis impossible.

[8] The CSRC has been authorized by the State Council to take enforcement actions against firms, managers, and

The CSRC and exchanges identify a company that may have engaged in misconduct through restatement announcements, anonymous tips, and news reports. Following certain investigation procedures, the CSRC and/or the exchanges determine whether the company and related parties have violated securities laws or other regulations.

The Enforcement Actions Research Dataset in the CSMAR database includes the announcement date of the fraud, the year during which the fraud was committed, the specific type of the fraud, and the enforcement agency. Given our focus on financial fraud, we only consider violations related to financial results, accounting misstatements, or accounting manipulations. Since financial results in each of the three years prior to the IPO year are disclosed in IPO fillings, we consider the fraud committed in the IPO year or three years before as an IPO fraud, consistent with Wang et al. (2010).

Table 2 provides descriptive information. Panel A reports the time trend of the IPO firm and the IPO fraud. The number of IPO firms is lower in 2014, 2018, and 2019, and higher in 2015 to 2017 and 2021 to 2022, consistent with the overall IPO trend during this period. 2.99 percent of IPO firms committed at least one type of financial fraud during the IPO process. Among the 34 unique IPO fraud firms, some engaged in fraudulent activities in only one year, while others committed fraud multiple times during the four-year period, so these 34 firms account for a total of 60 firm-year instances of fraud. Panel B shows that most of these instances occurred in the IPO year or the year before. Additionally, some firm-year observations involve more than one fraud type. Therefore, the 60 firm-year fraud observations account for a total of 185 fraud activities (each firm-year-fraud type is considered a fraud activity). Panel C provides an overview of the types of fraud activities. The identified fraud activities include profit manipulation, fabrication of assets, false statements, major failure to disclose information,

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other parties involved in violations of securities laws and regulations since August 17, 1993. On August 21, 1996, the Shanghai and Shenzhen Stock Exchanges were also authorized to issue stock exchange rules to regulate listed firms and related parties. The rules came into effect in January 1998.

accounting improprieties, and others.

3.3. Machine-based deception score

We employ machine learning techniques that are adept at handling high-dimensional data to construct a comprehensive visual deception score to detect deceptive behavior during IPO roadshows. The method of using machine learning techniques to detect deception from real-life videos has been applied in an emerging field of automated deception detection and has been shown to achieve significantly higher accuracy than humans (Gogate et al., 2017; Wu et al., 2018; Ding et al., 2019). Our video processing method involves four steps that are explained in detail in the following section.

3.3.1. Step 1: Decompose firm videos into individual videos

We combine the opening speech, Q&A session, and closing speech into one firm video. To decompose the firm videos into individual videos, we follow Hu and Ma (2023) and use images sampled at ten frames per second to identify and compare human faces. Specifically, we feed our raw images into the cloud computing system and receive a host of face-related measures. The face-detection API identifies faces in all images, while the face-comparison API compares two faces and determines whether they belong to the same individual, with an error rate of 0.001%.[9] Next, we compile and edit firm videos into several individual videos using a video editing package. We manually match each individual video to his/her company, position, name, and speech script provided on Quanjing's website. We only include individuals representing the IPO firm and exclude the individual videos of the hosts and underwriters. The process results in 3,298 individual videos from 1,138 firms. The median length of a firm executive video is 156 seconds, and the mean is 131 seconds.

[9] The face-detection and face-comparison machine-learning algorithms are provided by Face++, a leading AI firm in China.

3.3.2. Step 2: Extract features

We next construct a set of visual features. For the sake of replicability and transparency, we adopt a series of established open-source Python packages to extract visual features. Consistent with previous studies (Morales et al., 2017), we extract face features by using a computer vision and machine learning facial behavior analysis toolkit, OpenFace, provided by the CMU MultiComp Lab (Baltrušaitis et al., 2018).[10] OpenFace classifies the extracted visual features into four categories, including gaze-related information, head and face location details, face shape characteristics, and facial Action Units (AUs). Each category includes 35 to 348 features. The specific names and descriptions of the features in each category are detailed in Online Appendix A Table OA1. Figure OA1 in Online Appendix A provides an illustration of the OpenFace output.

To construct a feature matrix that can be processed by the machine learning algorithm, we estimate one feature vector for the visual dimension of each video using OpenMM, an open-source multimodal feature extraction tool.[11] According to OpenMM, it applies a series of statistical functions such as maximum, minimum, mean, 25th percentile, 50th percentile, and 75th percentile to each of the extracted features across all frames, summarizing the frame-level features into video-level features.[12]

3.3.3. Step 3: Build and evaluate the classification model

We train a machine-learning model to separate liars from truth-tellers. To this end, we need to have a dataset that has established deceptive and truthful labels for each individual's

[10] OpenFace is an open-source facial behavior analysis toolkit that has achieved state-of-the-art results in facial landmark detection, head pose estimation, facial action unit recognition, and eye gaze estimation. For more detailed information, see https://github.com/TadasBaltrusaitis/OpenFace.

[11] Detailed information can be found here: https://github.com/michellemorales/OpenMM/tree/openmm_v2.

[12] We focus on visual features only and control for the vocal and textual dimensions because we aim to show that visual component has incremental predictive power over existing textual and vocal cues in prior literature. As a robustness check, we train a multimodal-based deception score integrating textual, vocal and visual dimensions. Once we have the integrated model, we feed the IPO roadshow videos into the model and calculate a deception score based on video, audio, and textual information (VAT score). Results in Table OA2 in the Online Appendix A shows that the VAT score is also significant and positively related to fraud.

video. The Real-life Trial dataset, developed by Pérez-Rosas et al. (2015), contains 121 labeled individual videos of real deception and real truth during court trials and is widely used in the automated deception detection literature. The dataset includes recordings from 21 unique female and 35 unique male speakers, with their ages approximately ranging between 16 and 60 years. Out of these 121 videos, 61 of them are deceptive, while the remaining 60 are truthful.[13] Trial outcomes such as guilty verdict, non-guilty verdict, and exoneration are used to correctly label video clips as being deceptive or truthful. In some cases, deceptive videos are obtained from suspects denying their involvement in a crime, while truthful clips are taken from the same suspects answering questions related to verified facts. Witness testimonies that have been confirmed by police investigations are labeled as truthful, while testimonies in favor of guilty suspects are labeled as deceptive. We use the RLT data with established labels to train our lying detection algorithm for three main reasons: (1) The trial scenario, with multiple rounds of evidence collection and efforts by police and prosecutors, is arguably the most reliable setting for determining whether a person is lying in real-life situations. (2) The creators of the dataset put significant effort into selecting the videos and assigning labels. This dataset has been widely cited in subsequent machine learning research on deception detection, further demonstrating the credibility of the database and its labels. (3) Prior psychology research on deception detection and its neuroanatomical foundation suggests that there may exist some common facial features indicative of lies across different settings.[14]

[13] Videos in the RLT dataset are collected from public multimedia resources where trial hearing recordings are available and where truthful or deceptive behavior could be fairly observed and verified. The selection process for the videos is rigorous and adheres to strict guidelines. These guidelines require that the defendant or witness in the video be clearly identified, that their face be visible for most of the clip duration, and that the visual quality be clear enough to identify facial expressions.

[14] There might be differences in the general communication styles between the Chinese people and the U.S. people and between the court trials and the IPO roadshows. However, psychology literature suggests that many visual deception cues are universal across different cultures and settings. Generally speaking, as long as the machine-learnings model trained in the U.S. court trail data captures some deception cues that are universal to all cultures and settings, it may still serve as a good indicator for deception in financial market in China. If there are some visual deception cues that only work for one culture/setting (e.g., the U.S.) but not another (e.g., China) and is picked up by our model trained in one culture/setting, this should add noise to our deception score and bias against

To build the deception detection model, we first process the videos in the RLT dataset and use the procedures described in step two to extract features. Second, we train a deception-predicting model using the extracted features as input to predict the deception outcome. We employ Python to build and evaluate the Random Forest classification model as this classifier has shown better performance in prior studies that use feature extracting procedures similar to ours (Pérez-Rosas et al., 2015; Morales et al., 2017).[15] We use 10-fold cross-validation to evaluate the predictive model, and it achieves the following performance: AUC (0.8079), accuracy (0.7167), precision (0.7382), and recall (0.7214). AUC is the area under the ROC curve, which is a summary of the overall diagnostic accuracy, with values of 0.500 representing chance levels and 1.000 representing a perfectly accurate prediction model.[16] The performance of our model is consistent with existing automated deception detection literature.

3.3.4. Step 4: Calculate firm-level machine-based deception score

Based on the trained predictive model in step three and the input features of the roadshow videos extracted in step two, we calculate visual deception scores for each executive in the roadshow. These executives' individual deception scores are then used to calculate the firm-level deception score (*DECEP_V_FIRM_RAW)*, which is the average of all executives' deception scores. *DECEP_V_FIRM_RAW* has a mean of 0.553 and a standard deviation of 0.087.

finding results. Nonetheless, to mitigate the potential differences in communication styles, in our robustness tests we implement two types of transfer learning to reduce the disparities in the distributions of visual features between the two samples. Online Appendix B provides more details.

[15] Random Forest is a type of ensemble learning. In contrast to conventional machine learning techniques such as SVM, which generate a single estimator, ensemble learning models can improve performance by aggregating the predictions of multiple models. We use the Random Forest model because Morales et al. (2017), Wu et al. (2018), and Khan et al. (2021) find that it has higher accuracy compared to the decision tree model. Similar to our study, these papers used automatically extracted visual features. Additionally, Pérez-Rosas et al. (2015) demonstrate that the Random Forest classification model achieves higher accuracy for facial feature sets even using human-coded visual features. We later find that our results are robust to using decision tree models in section 6.

[16] The other performance metrics are accuracy, precision, and recall. Accuracy is the classification accuracy over the sample. Precision is the proportion of actual deception among those classified by the model as deception. Recall is the proportion of correctly predicted deception classified by the model among those actual deception.

4. Empirical results

To examine whether the machine-based deception score predicts fraud, we estimate the following Logit model:

$$\Pr(FRAUD) = \mathrm{F}(\beta_0 + \beta_1\, DECEPTION\_V\_FIRM + \beta_2\, Controls + Industry\ FE + Year\ FE) \quad (1)$$

where the dependent variable, *FRAUD*, is an indicator variable that captures the occurrence of financial fraud committed by a firm in IPO year or three preceding years. To allow the comparison of regression coefficients of the overall visual deception scores and the scores of different roadshow topics, we normalize all visual deception scores following Clement and Tse (2005) and Huang et al. (2017). *DECEPTION_V_FIRM* is the scaled transformation of *DECEP_V_FIRM_RAW* using the equation:

$$\text{Scaled } X = (X - \text{Min } X)/(\text{Max } X - \text{Min } X) \quad (2)$$

where X is raw visual deception score *DECEP_V_FIRM_RAW* and Min (Max) X represents its minimum (maximum) in our sample. The normalization process does not change our inferences in any way. The results of using raw visual deception scores are presented in Online Appendix A Table OA3. Table 3 presents descriptive statistics for the primary variables. As indicated, *DECEPTION_V_FIRM* exhibits sufficient variance.

Table 4 Column 1 presents a univariate assessment of how well the machine-based visual deception score (*DECEPTION_V_FIRM*) predicts IPO fraud (*FRAUD*). A positive and significant association is observed between IPO fraud and our deception score (z-stats = 5.860), indicating that the visual deception score is a significant predictor of IPO fraud. We then add control variables in Column 2. We control for performance-related variables — return on assets (*ROA*), leverage ratio (*LEV*), firm size (*SIZE*), and sales growth (*GROWTH*) (Chen et al., 2006; Hobson et al., 2012; Allee et al., 2021; Li et al., 2023), corporate governance variables — venture capital backing (*VC*), the duality of chairman and CEO (*DUALITY*), the number of board directors (*BOARD*), the proportion of shares owned by legal entities (*LEGAL*) and individuals (*INDV*), whether a firm has foreign stockholders (*FOREIGN*), the percentage ownership of the major stockholder (*TOP*), the Herfindahl index of stock ownership of the second through tenth largest owners (*TOP10_HHI*), auditor quality (*BIG10*), and the regional market development (*MARKETINDEX*) (Dechow et al., 1996; Farber, 2005; Chen et al., 2006; Stuart and Wang, 2016). Furthermore, we control the information content in IPO prospectuses (Hanley and Hoberg, 2010; Loughran and McDonald, 2013), which is available for download on an official disclosure platform for Chinese-listed companies.[17] Using the downloaded prospectuses, we calculate the percentage of risk-related words in the IPO prospectuses (*RISK_FILE*) and tone of firms' IPO prospectuses (*TONE_FILE*). We also include managers' negative facial emotions (*NEG_EMOTION*) in our regressions to ensure that our visual deception cues are not merely capturing observable facial emotions (Gong et al., 2019; Hu and Ma, 2023). Variable definitions are provided in Appendix A. We winsorize continuous variables at 1 percent and 99 percent and include both year and industry fixed effects in all regressions. Standard errors are clustered at the industry level.

The coefficient on the visual deception score remains significantly positive with comparable magnitude to that observed in the univariate model reported in Column 1. The predictive power of the machine-based visual deception score is not only statistically significant but also economically meaningful. Using the estimates in Column 2, we find that when the deception score increases from the first quartile (0.612) to the third quartile (0.780), with all other covariates fixed at their means, the probability of fraud increases from 2.43 percent to 3.92 percent, which represents a 61.32 ((3.92 − 2.43)/ 2.43) percent increase.

Next, we assess whether the predictive power of the visual deception cues is incremental

[17] www.cninfo.com.cn.

to financial-statement-, textual-, audio-, and picture-based predictors. First, we study the prediction power of other existing predictors by regressing *FRAUD* on other predictors including the financial-statement-based predictor in Dechow et al. (2011), *FSCORE*, lying word categories in Larcker and Zakolyukina (2012), *LIEWORD*, audio-based deception score, *DECEPTION_A_FIRM*, and picture-based fraud predictors facial masculinity following Jia et al. (2014), *FWHR*.[18] We further control for six financial-statement cues in Bao et al. (2020), *Bao et al. Predictors*,[19] textual predictors generated by five topics of IPO roadshow transcripts following Brown et al. (2020) and Blankespoor et al. (2023), *RS_TOPICS*, and other control variables included in Panel A. We report the results in Column 1, Panel B of Table 4. The visual deception score is then added in Column 2 along with the controls and other predictors. To assess the performance of the models with and without the visual deception score, we report the AUCs, following the methodology of Hobson et al. (2012). The results suggest that after adding the visual deception score in Column 2, the pseudo R-square increases from 0.162 to 0.176, and the AUC for the joint model (AUC = 0.8164) is higher than the AUC for the model without the video predictor (AUC = 0.8010), with the difference being statistically significant (Wald p-value < 0.01).

Additionally, we compare Type I and Type II errors and other classification performance

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[18] We use the list of lying word categories developed in Larcker and Zakolyukina (2012) to control for textual deception score. These word categories are based on psychosocial dictionaries Linguistic Inquiry and Word Count (LIWC) (Pennebaker et al., 2015). As our speech transcripts are in Chinese, we translate the English word categories into Simplified Chinese using the Simplified Chinese LIWC dictionary, which is kindly provided to us by Yitai Seih and James W. Pennebaker. As for audio analysis, Hobson et al. (2012) document that vocal markers of cognitive dissonance are useful for detecting financial misreporting. However, we are not able to replicate their exact vocal marker of cognitive dissonance as the automated vocal emotion analysis software they used, the Ex-Sense Pro R, is no longer available. Therefore, we control for audio predictor by constructing an audio deception score following Morales et al. (2017). See details in Appendix A.

[19] Bao et al. (2020) use 28 financial variables in their fraud-predicting model. They indicate that ten variables are most powerful in predicting fraud: common shares outstanding, current assets, sale of common and preferred stock, PP&E, accounts payable, cash and short-term investments, stock price, retained earnings, inventories, and common equity. After requiring the variables to be available in an IPO setting and correlations with other variables in our regressions to be no higher than 0.70 to avoid the multi-collinearity problem, we are left with six variables including current assets, accounts payable, cash and short-term investments, retained earnings, inventories, and common equity. Our results are robust to including all ten most powerful variables identified in Bao et al. (2020).

between the prediction model with visual deception score and the one without. Specifically, we investigate the classification performance for both models at various cutoff levels including 50th, 70th, and 90th percentiles of the predicted fraud probability distribution following Larcker and Zakolyukina (2012). If the 50th (70th/90th) percentile is used as the cutoff, an observation is assigned to the fraud category if the predicted fraud ability is above the 50th (70th/90th) percentile, and to the truthful case otherwise. Our results show that, for all cutoff levels, the Type 1 and Type 2 errors of the model in Column 1 are higher than those in Column 2, suggesting that including the visual deception score decreases both types of errors. Moreover, the true positive rate, precision, and accuracy are higher for the model with the deception score in Column 2 than for the model without the deception score in the Column 1. Details can be found in Online Appendix A Table OA4. Overall, the results using various model performance evaluation measures suggest that the model combining the machine-based visual deception score with other existing predictors performs significantly better at predicting fraud than existing models without the visual deception score.

Our analyses above indicate that the machine-based visual deception score during IPO roadshows has significant predictive power for IPO fraud. One possible reason is that the managers who have committed financial frauds lie during the roadshows, leaving subtle cues captured by our machine-based deception score. Under the logic, the deception cues during the discussions of the materials related to financial performance should have more predictive power for the financial-related fraud. We test the conjecture by decomposing the deception score into topic-oriented scores using the video portions of executives discussing different topics during roadshow presentations. We explore whether the variation of the deception score ex-ante effectively reveals the type of the on-going fraud unraveled ex post.

We use a speech recognition toolkit, Vosk, to extract speech transcriptions of roadshow videos, including a list of words, time stamps (onsets and offsets) of these words, and punctuation. We then decompose firm-level video into sentences by using those timestamps and punctuation marks and calculate the machine-based visual deception score of each sentence video. We employ a Bayesian topic modeling algorithm, termed Latent Dirichlet Allocation (LDA) on the speech transcript to generate five topics and the weight for each word associated with each of the five topics. The deception score for topic1, *DECEP_TP1*, is the sum of all sentences' machine-based visual deception scores multiplied by the sentence's weight of topic 1, normalized to range between zero and one using equation (2). The deception scores for topic2 – topic5 are defined in the same way and labeled as *DECEP_TP2 – DECEP_TP5.*

Next, we investigate whether the variation of deception scores across different topics has meaningful links to the type of fraud being committed and later revealed. Results are presented in Table 5. In Column 1, we replace the overall deception score with the score based on the discussion on financial results (topic 1) in the regression, the coefficient on the score on financial topic is significant and positive. In Columns 2 to 5, we include the deception scores based on other topics. Given that our focus is on financial related fraud, we do not expect the deception scores of other topics to be significant predictors. For example, even if a firm has engaged in financial fraud such as profit manipulation, they may still truthfully discuss their technology and brand. Consistently, we find that the deception scores of other topics are insignificant both statistically and economically, and the levels of AUCs achieved by models with visual deception scores from other topics are similar to that achieved by the model without any visual deception score in Column 1 of Panel B Table 4. By contrast, the model with visual deception score based on the discussion of the financial results achieves a statistically greater AUC (Column 1, AUC = 0.8147) than the model without it (Column 1 of Panel B Table 4, AUC = 0.8010), and the p-value for the difference is 0.0538. The level of the AUC of Column 1 is similar to the level of the AUC of Column 2 of Panel B Table 4 achieved using the deception score of the overall video (AUC = 0.8164). In Column 6, we include all five deception scores into the regression. The model achieves the highest AUC at 0.8331, significantly higher than the model without any visual predictors in Column 1 of Panel B Table 4, with a p-value of 0.0042. Most importantly, we find that the deception score based on the discussion of the financial results is the only deception score that is significantly positive while the deception scores of all the other four topics are not statistically significant.

Overall, the above evidence shows that the type of the on-going fraud unraveled ex post is predicted particularly by the visual deception score during the discussion of related materials. It demonstrates that our machine-based deception score captures more subtle information beyond manager-level of firm-level characteristics. Specifically, our visual deception score may vary across different topics within a manager's roadshow presentation in a way that potentially reveals the type of the fraud being committed, which a lying characteristic measured at the manager/firm level cannot accomplish.

5. Inner workings of the machine-learning model

To mitigate the concern on the black box nature of machine learning approach, in this section, we explore how our machine-based deception score makes predictions, i.e., understand what features contribute to the deception outcome. We first conduct a Principal Component Analysis (PCA) on the models' input visual features and obtain six representing components. Next, we assess the importance of these components in our machine learning model, connecting them to the determinants of lies documented in psychological literature and the task of fraud detecting in financial contexts.

Panel A of Table 6 describes the six components. Based on the area of the features with top loadings generated by PCA, we name each principal component in the second column. Detailed loadings are provided in Appendix B. We then list the relevant support that each component area receives from the psychology literature in the third column. To better understand the importance of these components in our machine learning model trained in the RLT database, we sum the model importance of the features that rank in the top 50 by their PCA loadings within each component and then rank the calculated model importance of each component in the last column.[20]

As shown in the table, among all six components, PCA1 (Face and Mouth Movement) ranks first by feature importance. The result aligns with the findings in previous psychology research that face and mouth movements have been found to be useful for deception detection (DePaulo et al., 2003; Bartlett et al., 2014; Khan et al., 2021; Shuster et al., 2021). PCA 4 (Brow and Gaze Movement), PCA 5 (Mouth and Cheek Movement) and PCA 6 (Genuine Smile) rank second to fourth by feature importance.[21] Consistently, the movements in these areas have been extensively documented as indicative of deception by prior research in psychology. For example, Ekman et al. (1985) and Craig et al. (1991) find that faked expression is related to more brow lowering and more upper lip raising. Shen et al. (2021) and Nam et al. (2022) show that lip stretching decreases when lying. In addition to facial AUs, researchers have extensively studied eye movements as a potential deception cue. Several studies (Janisse and Bradley, 1980; Lubow and Fein, 1996; DePaulo et al., 2003; Cook et al., 2012) have found that liars tend to have more dilated pupils and more gaze aversion (or fewer fixations). Additionally, individuals who lie tend to exhibit fewer genuine smiles, making genuine smiling a potential predictor of non-deception (Ekman, 1985/2001; DePaulo et al., 2003; Monaro et al., 2022).

By contrast, PCA 2 (Nose Movement) and PCA 3 (Chin Movement) both have very low feature importance in our model, which is consistent with the very limited psychology literature that suggests connections between the visual cues in these areas and deception. There is only

[20] The ranking of these components' model importance does not change if we alternatively sum the feature importance using the features that rank in the top 20 or 80 by their PCA loadings within each component.

[21] A genuine smile, also known as a Duchenne smile, is a type of smile that involves the contraction of the orbicularis oculi muscle around the eyes (AU06).

one exception — DePaulo et al. (2003), which suggests that chin raises are positively related to deception. Overall, the above analyses indicate that the features that are important in our machine learning model also have strong support from psychology research whereas those features that rank low by the machine learning model have very limited or no support from psychology research. These suggest that our machine learning models indeed pick up features that are shown by prior psychology literature to be related to deception.

Next, we examine whether these components are related to fraud prediction in financial contexts. Panel B of Table 6 shows significantly positive coefficients on Face and Mouth Movement and significantly negative coefficients on Brow and Gaze Movement, Mouth and Cheek Movement, and Genuine Smile with or without the same control variables and other predictors in Panel B of Table 4. The findings suggest that the cues that are important in our machine learning model and have strong support from psychology research significantly predict fraud in IPO roadshow setting. By contrast, the features that have limited support from psychology research and are not weighed heavily in our machine learning models are not significant predictors of lies in financial context either.

In sum, our analyses in this section build connections among three important elements of our paper — the deception detection machine learning models trained using RLT data, the existing psychology research on deception, and the fraud prediction in the IPO roadshow setting. The identification of a common set of important features confirms that the features crucial for detecting lying in court trials are also significant for detecting financial fraud. Our machine learning model successfully identifies these features. Additionally, the analyses support prior psychology research indicating that there may exist deception features that are universal across settings, cultures, and races.

6. Additional analyses

6.1. Managers' incentives

To further understand managers' incentives to deceive during IPO roadshows, we examine whether managers' stock sales in post-IPO period and the stock market performance vary with firm's deception score. Specifically, we analyze managers' stock sales around the expiration of the lock-up period, which typically occurs one year after the IPO date, and the subsequent stock returns. In Table 7, we examine managers' sales in 10, 20, 60 trading days after the lock period expires. The results indicate that the deception score is positively associated with stock sales in the 10 and 20 trading day windows, suggesting that managers from the firms with higher deception scores rush to sell more shares immediately after the lock period expires. Consistently, the cumulative abnormal returns in the 60 and 120 trading days after the expiration of the lock up period are negatively associated with the deception score, whereas the coefficients for returns in the 20 days are not significant. This suggests that the long-run stock market performance of firms with higher deception is worse. The results suggest that managers with higher deception scores might be aware of the on-going financial fraud and anticipate the eventual poor fundamental performance at the firm, so they sell their shares immediately after they are allowed to do so. The results that the managers from the firms with higher deception scores sold their shares earlier and that the post-lock-up-period stock performance for these firms is worse than other firms suggest these managers avoid potential losses.

6.2. Machine vs Human

Unlike machines, humans may find it more difficult to combine or incorporate high-dimensional features. Next, we examine whether investors and regulators incorporate our machine-based deception score in their decisions. We regress IPO initial returns and the regulator's inquiry letter dummy variable on our deception score. The results are shown in Online Appendix A Table OA5. The coefficients on the machine-based deception score are not significantly different from zero, suggesting that neither investors nor regulatory agencies incorporate the deception cues in roadshow presentations. The results support our conjecture that the machine learning model captures deception cues in videos while humans fail to do so.

6.3. Construct validity

To assess the validity of our deception score, we employ a series of pseudo analyses leveraging a natural pseudo group, i.e., hosts of IPO roadshows. Our video data contains not only firm managers but also hosts who have no incentive to deceive but speak for a longer time than firm managers.[22] If our machine learning algorithm correctly identifies deception, the deception score of hosts should be significantly lower than that of managers and unrelated to fraud. We find that the average normalized deception score of hosts is 0.380, which is indeed significantly lower than that of managers 0.635 (Mean Diff = 0.255, *t*-value = 45.034). In addition, we re-estimate model (1) in Table 4 by replacing the deception score of managers with that of hosts. The results, presented in Panel A of Table 8, indicate that the deception score of hosts is not statistically significant for IPO fraud, which is consistent with their lack of inside information and incentive to deceive investors during roadshows.

6.4. Robustness tests

We acknowledge that our deception detection model is trained using court trial videos in the RLT database and applied to IPO roadshow setting in China. We make this design choice

[22] The median (mean) length of a host's video is 215 (219) seconds, longer than an executive video. This is expected as the host needs to introduce roadshow participants and provide information about the new share issuance, including the price per share, the number of new shares, and the operating performance.

because nonverbal behaviors and facial expressions of different emotions (e.g., emotions associated with lies) are universal, the same for all people regardless of age, sex, race, or culture. Nevertheless, we further address this concern by employing transfer learning, especially semi-supervised learning and adversarial domain adaptation (Domain-Adversarial Neural Network, DANN). We detail these two methods in Online Appendix B. Figure OB1 illustrates that the difference between the training domain and test domain is minimized after the domain adaptation. The results in Table OB1 show that our results are robust to addressing the differences between the videos in the RLT database and our roadshow videos.

Furthermore, to ensure that our results do not rely on a specific machine learning classifier, we employ alternative machine learning classifiers, i.e., Gradient Boosting Decision Tree (GBDT) classifier and Multi-Layer Perceptron (MLP) model, to calculate the deception score. Results shown in Column 1 and 2 of Panel B Table 8 indicate that our findings are robust to the alternative machine learning classifiers.

In addition, because the construction of our main independent variable averages all executives' deception scores, we examine whether our results are robust using a duration-weighted deception score. Column 3 of Panel B Table 8 shows that the duration-weighted deception score is also positive and significant. Moreover, since the use of a teleprompter does not definitely preclude a speaker from reading scripts in Quanjing, we quantitatively assess the likelihood of head-lowering (indicative of reading from transcripts) in our data using the OpenFace package. Specifically, we analyzed the gaze direction (gaze_angle_y) and head rotation (pose_Rx) features to identify instances of head-lowering. [23] We find that the duration

[23] We validate this approach by asking a RA to locate lowering heads for a random sample 100 IPO roadshows (251 individual videos). We notice that executives often nod their heads, as a polite gesture, when being introduced by the host and then ask RA to locate the exact timestamp that executives first nod their heads. Results show that the mean (median) of timestamp of the first nod is 4.66 (4.50). Therefore, when identifying head-down script-reading behavior rather than nodding as a polite gesture, we only consider instances where the head-down action occurs after the first 5 seconds of the individual video. The accuracy of our approach in identifying whether an executive is lowering their head in a specific frame is 79.17%.

of these head-lowering only accounts for 6.76% of the total video time. In Column 4 of Panel B Table 8, our results are robust after excluding the portion of the video that contains lowering heads.

When defining IPO fraud, we include fraud committed during the IPO year to be consistent with existing research on IPO fraud.[24] To ensure that our results are not driven by fraud committed after the IPO date, we spend some efforts to obtain a more precise estimate of when actual fraud happens during the IPO year, before or after the IPO date. To do so, we search news articles and firm announcements of the IPO-year fraud cases. Among all the 34 IPO fraud firms identified, 31 are found to have committed fraud during the IPO year (as illustrated in Table 2 Panel B). 13 out of these 31 firms started committing fraud before the IPO year, while the remaining 18 firms started fraud during the IPO year. We further examine these 18 firms to identify when the fraud is committed within the IPO year. Our investigation indicates that, out of these 18 firms, nine firms engaged in fraudulent activities before the IPO date. Out of the remaining nine firms, all but one firms' fraud periods cover the IPO dates (e.g., IPO in March and Q1 reports contain fraudulent information). These fraud cases are most likely related to the firms' IPOs. Nonetheless, to ensure that our results are not driven by these nine remaining observations, we exclude them in the analyses reported in Panel C of Table 8. Our results are robust.

Fifth, we check the robustness of our results to alternative ways of controlling financial-based and text-based features. Our results are robust to alternatively controlling textual predictors generated by 31 topics of IPO prospectuses (Brown et al., 2020) and financial variables suggested by Cecchini et al. (2014) in Column 1 and Column 2 of Panel A of Online Appendix A Table OA6, respectively.

[24] One technical reason is that standard databases such as CSMAR only provide the year when a fraud is committed rather than the actual fraud date.

Finally, we check and find that our results are robust to alternative ways of fixed effects and clustering standard errors. The details of these analyses are presented in Panel B of Online Appendix A Table OA6. In addition, our results are robust to dropping of any single year, industry, or province from the sample.

7. Conclusions

Discovering financial fraud in time is important for investors, creditors, auditors, and regulators. While prior studies have exploited various predictors of financial fraud using structured data and unstructured data, few studies examine the visual dimension of nonverbal cues. We take advantage of the mandatorily disclosed IPO roadshow videos in China along with advanced facial recognition and machine learning techniques to provide evidence on the usefulness of visual deception cues in predicting fraud. Our results indicate that the machine-based visual deception score during IPO roadshows predicts IPO fraud, even after controlling for financial statement-, audio-, and textual-based fraud predictors. Visual information provides incremental predictive power over existing predictors, suggesting expressions and motions capture additional cues of deception.

Furthermore, the type of the on-going fraud unraveled ex post is predicted particularly by the visual deception score during the discussion of related materials, indicating that our machine-based deception score captures more subtle information beyond a manager level measure of the innate lying tendency. To address the black box nature of machine learning and further understand the mechanism of our results, we first investigate how the video cues used in the deception detection machine learning models are connected to the psychology research on deception. To reduce the extremely high dimensions of all visual features, we use PCA to obtain six principal components representing the feature set. Our results show that only the principal components that have strong support from existing psychology research as indicators for deception, including face and mouth movements, brow and gaze movements, mouth and cheek movements and genuine smiles, are heavily relied on by the machine learning model, while the other components that have little psychology support are weighted less in the model. This suggests that the machine learning model indeed captures deception cues well-grounded in the psychology literature. The fact that our model trained in RLT setting works well in the IPO setting suggests that some deception features are universal across contexts, cultures, and races.

Our finding has important implications for regulators and corporate monitors. Investors with mandatory video disclosure could consider turning to machine-trained visual deception models to help assess the likelihood of fraud. Regulatory agencies may take into account the incremental benefits of using visual information for early fraud detection.

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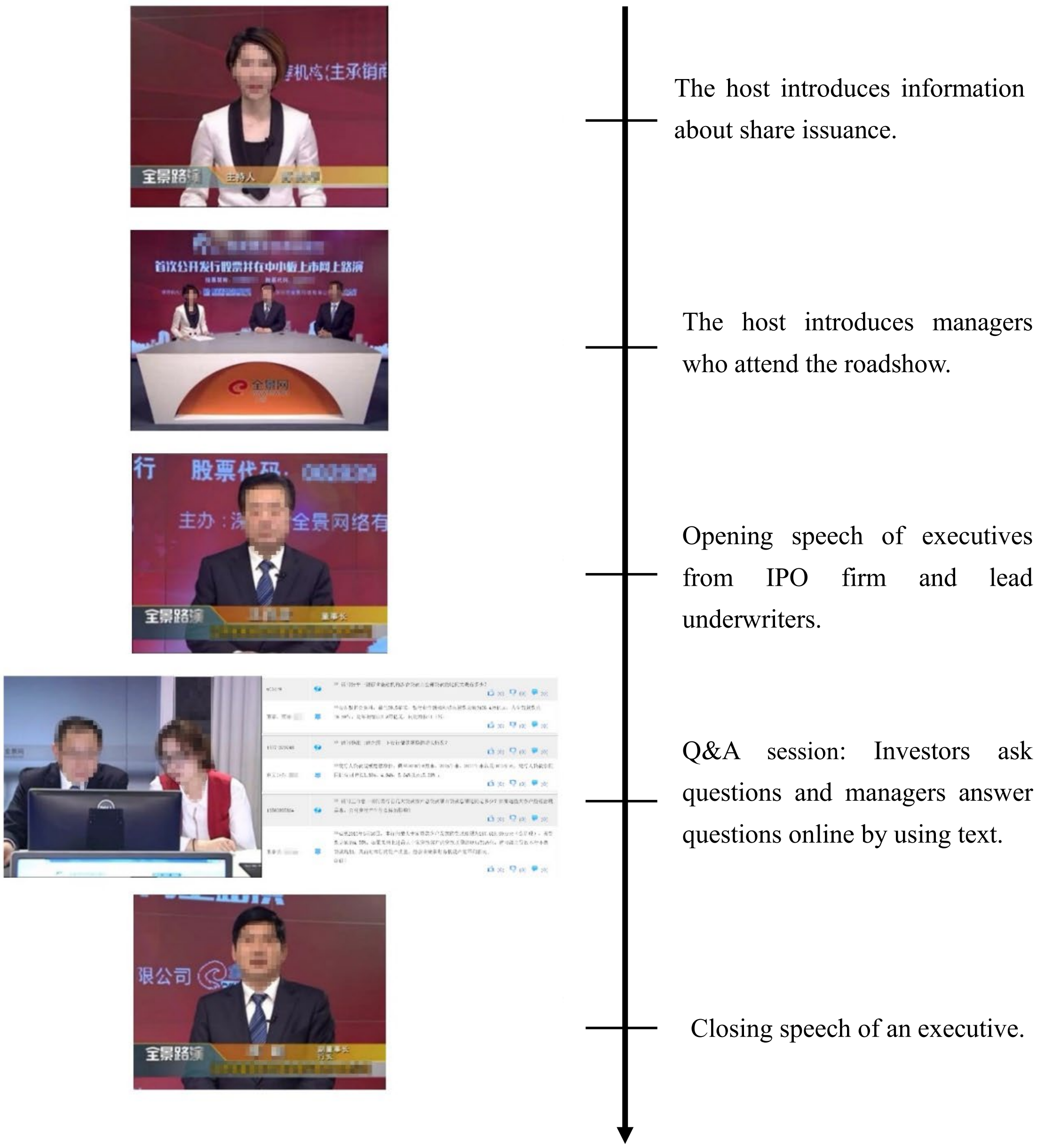

Fig. 1. Chinese IPO roadshow

Figure 1 illustrates the Chinese IPO roadshow process. For privacy protection, we pixelate the faces in the video.

Table 1 Sample selection and distribution

Panel A. Sample Selection	
	No. of observations
Chinese firms that completed an original initial public offering on the Shenzhen Stock Exchange between January 1, 2014, and December 31, 2022	1,269
Less:	
Firms that we are unable to download roadshow videos	(66)
Downloaded roadshow videos are damaged or cannot be analyzed	(29)
Observations from the financial sectors	(13)
Missing data for control variables used in the regression	(23)
Final	1,138

Panel B. Descriptive Statistics for Firm Videos

Variable	*N*	MEAN	*SD*	P25	P50	P75
PERSON COUNT	1,138	6.00	1.38	5	6	7
CHAIR	1,138	0.96	0.20	1	1	1
CEO	1,138	0.81	0.40	1	1	1
CFO	1,138	0.73	0.44	0	1	1
SOB	1,138	0.78	0.41	1	1	1
UNDERWRITER	1,138	1.51	0.62	1	2	2

Panel A of Table 1 details our sample selection process and reports the final number of IPO firms included in our empirical analyses. Panel B provides descriptive statistics on the attending executives of firm IPO roadshows. *PERSON COUNT* is the total number of participants in the firm's IPO roadshow video. *CHAIR* (*CEO*/*CFO*/*SOB*) represents an indicator variable that equals one if the Chair (CEO/CFO/SOB) of the firm participates in the internet roadshow, zero otherwise. SOB is the secretary of the board. *UNDERWRITER* is the number of participants from the underwriter investment bank.

Table 2 Fraud distribution

Panel A. Fraud Distribution by IPO Year

Year	Fraud firm (A)	IPO firm (B)	Percentage (A/B)
2014	5	66	7.58
2015	7	128	5.47
2016	3	128	2.34
2017	4	197	2.07
2018	4	42	10.26
2019	1	70	1.47
2020	1	159	0.63
2021	7	210	3.35
2022	2	152	1.34
Total (Mean)	34	1,138	(2.99)

Panel B. Fraud distribution by the fraud commitment year relative to the IPO year

Year	Observations	Fraud instances	Percentage
T-3	1,138	6	0.53
T-2	1,138	8	0.70
T-1	1,138	15	1.32
T(IPO year)	1,138	31	2.72
Total	-	60	-

Panel C. Fraud distribution by type

Fraud Type	Frequency	Percentage
Profit manipulation	18	9.73
Fabrication of assets	4	2.16
False statements	64	34.59
Major failure to disclose information	51	27.57
Accounting improprieties	42	22.70
Others	6	3.24
Total	185	100

Table 2 provides descriptive information about fraud in our sample.

Table 3 Descriptive statistics

Variable	*N*	MEAN	*SD*	P25	P50	P75
FRAUD	1,138	0.030	0.170	0.000	0.000	0.000
DECEPTION_V_FIRM	1,138	0.553	0.087	0.510	0.566	0.615
FSCORE	1,138	1.297	0.616	0.868	1.178	1.576
LIEWORD	1,138	0.049	0.011	0.041	0.048	0.056
DECEPTION_A_FIRM	1,138	0.497	0.055	0.456	0.495	0.535
FWHR	1,138	2.016	0.475	1.681	2.162	2.245
SIZE	1,138	20.509	0.789	19.982	20.369	20.889
ROA	1,138	0.131	0.069	0.086	0.120	0.161
LEV	1,138	0.384	0.159	0.262	0.381	0.496
VC	1,138	0.723	0.448	0.000	1.000	1.000
DUALITY	1,138	0.322	0.467	0.000	0.000	1.000
BOARD	1,138	2.190	0.162	2.079	2.303	2.303
NEG_EMOTION	1,138	2.896	13.276	-3.040	2.063	8.067
TONE_FILE	1,138	2.413	0.522	2.072	2.405	2.738
RISK_FILE	1,138	0.548	0.105	0.479	0.545	0.614
IND	1,138	0.162	0.213	0.000	0.000	0.333
GROWTH	1,138	0.220	0.272	0.059	0.170	0.308
LEGAL	1,138	0.364	0.291	0.120	0.277	0.602
INDV	1,138	0.113	0.131	0.000	0.072	0.180
FOREIGN	1,138	0.133	0.339	0.000	0.000	0.000
TOP1	1,138	47.284	17.677	34.420	45.842	58.710
TOP10_HHI	1,138	0.058	0.042	0.026	0.049	0.081
MARKETINDEX	1,138	7.290	1.096	6.580	7.760	7.970
BIG10	1,138	0.616	0.487	0.000	1.000	1.000

Table 3 provides descriptive statistics. *N* represents the number of observations, *SD* represents the standard deviation, and P25 (P75) represents the 25th (75th) percentile of the variable's distribution. All variables are defined in Appendix A. All continuous variables are winsorized at the top and bottom 1 percent.

Table 4 Machine-based visual deception score and financial fraud

Panel A. Machine-Based Visual Deception Score and Financial Fraud		
	(1)	(2)
	FRAUD	*FRAUD*
DECEPTION_V_FIRM	3.177***	3.130***
	(5.860)	(6.369)
SIZE		0.204
		(0.675)
ROA		-1.649***
		(-2.754)
LEV		1.515
		(0.941)
VC		0.975***
		(4.008)
DUALITY		0.275
		(1.597)
BOARD		1.072
		(0.939)
NEG_EMOTION		0.000
		(0.023)
TONE_FILE		0.366*
		(1.853)
RISK_FILE		-0.346
		(-0.369)
IND		-0.741
		(-0.941)
GROWTH		0.172
		(0.397)
LEGAL		-0.395
		(-0.884)
INDIV		-1.174
		(-1.160)
FOREIGN		0.221
		(0.440)
TOP		-0.007
		(-0.726)
TOP10_HHI		-8.399***
		(-3.156)
MARKETINDEX		0.146
		(0.672)
BIG10		-0.447***
		(-3.231)
Industry FE	Yes	Yes
Year FE	Yes	Yes
N	1,138	1,138
Pseudo R^2	0.098	0.154

Panel B. Compare Machine-Based Visual Deception Score and Existing Predictors		
	(1) *FRAUD*	(2) *FRAUD*
DECEPTION_V_FIRM		3.433***
		(9.511)
FSCORE	0.173	0.176
	(1.285)	(1.314)
LIEWORD	5.953	4.932
	(0.732)	(0.679)
DECEPTION_A_FIRM	3.807*	4.163**
	(1.927)	(2.002)
FWHR	-0.182	-0.244
	(-0.662)	(-0.895)
Bao et al. Predictors	Yes	Yes
RS_TOPICS	Yes	Yes
Controls	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
N	1,138	1,138
Pseudo R^2	0.162	0.176
AUC[a]	0.8010	0.8164
p-value for AUC=0.500	<0.001	<0.001

Table 4 provides the logistic regression results for our machine-based deception score and fraud. Panel A reports the results of the following Logit regression:

$$\Pr(FRAUD) = F(\beta_0 + \beta_1\, DECEPTION\_V\_FIRM + \beta_2\, \text{Controls} + Industry\ FE + Year\ FE)$$

where the dependent variable *FRAUD* is an indicator variable that takes the value of one if a firm has committed financial fraud during the IPO process, and zero otherwise. *DECEPTION_V_FIRM* is our machine-based deception score predicted by using visual features, see details in section 3.3. Panel B reports the results of comparing machine-based visual deception score and existing predictors, including financial, text, audio predictors and roadshow topics generated by LDA analysis. Bao et al. Predictors refer to six financial-statement cues in Bao et al. (2020), including *CASH, CURRASSET, RETEARN, PAYABLE, INV, EQUITY*. RS_TOPICS refer to five variables that measure the topics distribution of roadshow transcripts.

All variables are defined in Appendix A. Standard errors are clustered by industry. *Z*-statistics are reported in parentheses. ***, **, * denote significance at 1 percent, 5 percent, and 10 percent levels, respectively.

[a] The receiver operating characteristic (ROC) curve analysis is used to quantify the accuracy of classifying IPO firms as having committed fraud or not. This area measures the global performance of the test. A greater area under the ROC curve (AUC) indicates better performance. The test statistic for testing whether the AUC is statistically different from the chance of 0.50 is (AUC − 0.50)/standard error (AUC), and two-sided *p*-values are reported.

Table 5 Decomposing machine-based deception score by topics of sentences

	(1)	(2)	(3)	(4)	(5)	(6)
	FRAUD	*FRAUD*	*FRAUD*	*FRAUD*	*FRAUD*	*FRAUD*
DECEP_TP1	3.620***					5.764***
(Financial, Risk)	(4.082)					(8.207)
DECEP_TP2		1.602				3.058
(Production, Advantage)		(0.615)				(0.653)
DECEP_TP3			0.238			1.138
(Brand, Opportunity)			(0.182)			(0.505)
DECEP_TP4				-0.475		-11.868
(Capability, Technology)				(-0.122)		(-1.548)
DECEP_TP5					-0.317	-0.578
(Project, Construction)					(-0.053)	(-0.123)
OTHER PREDICTORS	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,138	1,138	1,138	1,138	1,138	1,138
Pseudo R^2	0.176	0.162	0.162	0.162	0.162	0.187
AUC[a]	0.8147	0.8007	0.8004	0.8020	0.8015	0.8331
p-value for AUC=0.500	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001

Table 5 presents the results of decomposing roadshows by topics generated by LDA analysis. This table reports the results of the following Logit regression:

Pr (*FRAUD*) = F ($\beta_0 + \beta_{1\text{-}5}$ *DECEP_TP1 (2/3/4/5)* + β_6 Controls + *Industry FE*+ *Year FE*)

where the dependent variable *FRAUD* is an indicator variable that takes the value of one if a firm has committed financial fraud during the IPO process, and zero otherwise. *DECEP_TP1 (2/3/4/5)* is the sum of all sentences' visual deception scores multiplied by the sentence's weight of topic1 (2/3/4/5). The sentence's visual deception score is predicted by the trained random forest model using visual features of the sentence video. All normalized to between 0 and 1. See section 3.3 for details. We include control variables as the Panel B Table 4 in all regressions. *OTHER PREDICTORS* include *FSCORE* in Dechow et al. (2011), six financial-statement cues in Bao et al. (2020), *Bao et al. Predictors*, lying word categories in Larcker and Zakolyukina (2012), *LIEWORD*, textual predictors generated by five topics of IPO roadshow transcripts following Brown et al. (2020) and Blankespoor et al. (2023), *RS_TOPICS*, audio-based deception score, *DECEPTION_A_FIRM*, and picture-based fraud predictors facial masculinity following Jia et al. (2014), *FWHR*. All variables are defined in Appendix A. Standard errors are clustered by industry. Z-statistics are reported in parentheses. ***, **, * denote significance at 1 percent, 5 percent, and 10 percent levels, respectively.

Table 6 Understanding inner workings of machine-based visual deception score

Panel A. Principal Components

PCA	Name	Supporting Evidence from Literature	Rank
PCA1	Face and Mouth Movement	DePaulo et al. (2003); Bartlett et al. (2014); Khan et al. (2021); Shuster et al. (2021)	1
PCA2	Nose Movement	N/A	5
PCA3	Chin Movement	DePaulo et al. (2003)	6
PCA4	Brow and Gaze Movement	Ekman et al. (1985); Vrij et al. (2000); Vrij (2008); Cook et al. (2012); Arminjon et al. (2015); Su et al. (2016); Constâncio et al. (2023)	2
PCA5	Mouth and Cheek Movement	DePaulo et al. (2003); Bartlett et al. (2014); Shen et al. (2021); Nam et al. (2022)	3
PCA6	Genuine Smile	Ekman (1985/2001); DePaulo et al. (2003); Monaro et al. (2022)	4

Panel B. Principal Components and Financial Fraud

	(1) *FRAUD*	(2) *FRAUD*
Face and Mouth Movement	0.069*	0.078*
	(1.789)	(1.814)
Nose Movement	0.034	0.047*
	(1.255)	(1.663)
Chin Movement	-0.054	-0.046
	(-0.753)	(-0.511)
Brow and Gaze Movement	-0.209***	-0.230***
	(-3.335)	(-4.933)
Mouth and Cheek Movement	-0.133**	-0.165**
	(-2.155)	(-2.343)
Genuine Smile	-0.284**	-0.350***
	(-2.533)	(-3.092)
OTHER PREDICTORS	No	Yes
Controls	No	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
N	1,138	1,138
Pseudo R^2	0.112	0.192

Table 6 explores the inner workings of our machine learning model. We apply principal component analysis and obtain six PCA components (PCA1-PCA6) to represent the input feature set. Each PCA component is labeled based on the corresponding area represented by the input feature set using the feature loadings. Panel A reports the name of each component, how much support each component area receives from prior psychology literature and the rank of the component's model importance. Panel B reports the regression of *FRAUD* on the six PCAs. We include control variables and predictors as listed in Column 2 of Panel B Table 4 in Column 2. *OTHER PREDICTORS* include *FSCORE* in Dechow et al. (2011), six financial-statement cues in Bao et al. (2020), *Bao et al. Predictors*, lying word categories in Larcker and Zakolyukina (2012), *LIEWORD*, textual predictors generated by five topics of IPO roadshow transcripts following Brown et al. (2020) and Blankespoor et al. (2023), *RS_TOPICS*, audio-based deception score, *DECEPTION_A_FIRM*, and picture-based fraud predictors facial masculinity following Jia et al. (2014), *FWHR*. All variables are defined in Appendix A. Standard errors are clustered by industry. *Z*-statistics are reported in parentheses. ***, **, * denote significance at 1 percent, 5 percent, and 10 percent levels, respectively.

Table 7 Machine-based visual deception score and stock market performance

	(1)	(2)	(3)	(4)	(5)	(6)
	STOCK_SALES $_{EXPPOST10DAY}$	*STOCK_SALES* $_{EXPPOST20DAY}$	*STOCK_SALES* $_{EXPPOST60DAY}$	$BHAR_{EXPPOST20DAY}$	$BHAR_{EXPPOST60DAY}$	$BHAR_{EXPPOST120DAY}$
DECEPTION_V_FIRM	0.222**	0.459**	0.349	-0.016	-0.100***	-0.127***
	(2.439)	(2.592)	(0.981)	(-1.161)	(-5.085)	(-4.400)
MOM_6M	-0.066	-0.146**	-0.235**	-0.025***	-0.028**	-0.045***
	(-1.701)	(-2.162)	(-2.447)	(-3.694)	(-2.554)	(-8.280)
OTHER PREDICTORS	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,138	1,138	1,138	1,138	1,138	1,138
R^2	0.047	0.058	0.083	0.103	0.130	0.144

Table 7 reports the results of the following OLS regression:

$$STOCKSALES \text{ or } BHAR = \beta_0 + \beta_1\ DECEPTION\_V\_FIRM + \beta_2\ Controls + Industry\ FE + Year\ FE + \varepsilon$$

where $STOCKSALES_{EXPPOST10DAY}$ ($STOCKSALES_{EXPPOST20DAY}$ or $STOCKSALES_{EXPPOST60DAY}$) is the total amount of roadshow managers' stock sales over a 10-trading-day (20-trading-day or 60-trading-day) window that starts on the IPO lock-up expiration date and is calculated as the number of stocks sold multiplied by the sold price scaled by the market value (in thousands) at the time lock-up period expires. $BHAR_{EXPPOST10DAY}$ ($BHAR_{EXPPOST20DAY}$, $BHAR_{EXPPOST60DAY}$ or $BHAR_{EXPPOST120DAY}$) is a firm's buy-and-hold market-adjusted returns over a 10-trading-day (20-trading-day, 60-trading-day or 120-trading-day) window that starts on the IPO lock-up expiration date. *DECEPTION_V_FIRM* is our machine-based deception score predicted by using visual features, see details in section 3.3. We include control variables and predictors as listed in Column 2 of Panel B Table 4 in all regressions. *OTHER PREDICTORS* include *FSCORE* in Dechow et al. (2011), six financial-statement cues in Bao et al. (2020), *Bao et al. Predictors*, lying word categories in Larcker and Zakolyukina (2012), *LIEWORD*, textual predictors generated by five topics of IPO roadshow transcripts following Brown et al. (2020) and Blankespoor et al. (2023), *RS_TOPICS*, audio-based deception score, *DECEPTION_A_FIRM*, and picture-based fraud predictors facial masculinity following Jia et al. (2014), *FWHR*. Standard errors are clustered by industry. *T*-statistics are reported in parentheses. ***, **, * denote significance at 1 percent, 5 percent, and 10 percent levels, respectively.

Table 8 Robustness results

Panel A. Construct Robustness			
	(1) *FRAUD*	(2) *FRAUD*	(3) *FRAUD*
DECEPTION_V_HOST	0.322	0.085	-0.065
	(0.617)	(0.124)	(-0.095)
OTHER PREDICTORS	No	No	Yes
Controls	No	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	1,136	1,136	1,136
Pseudo R^2	0.085	0.142	0.162

Panel B. Measurements of deception scores				
	(1) *FRAUD*	(2) *FRAUD*	(3) *FRAUD*	(4) *FRAUD*
DECEPTION_V_GBDT	2.702***			
	(5.031)			
DECEPTION_V_MLP		1.604***		
		(2.765)		
DECEPTION_V_DurationWeight			2.909***	
			(5.608)	
DECEPTION_V_NoLowerHead				2.603***
				(2.888)
OTHER PREDICTORS	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	1,138	1,138	1,138	1,138
Pseudo R^2	0.171	0.168	0.172	0.171

Panel C. Robustness regarding IPO-Year fraud			
	(1) *FRAUD*	(2) *FRAUD*	(3) *FRAUD*
DECEPTION_V_FIRM	1.990***	2.099***	2.869***
	(3.005)	(2.846)	(4.736)
OTHER PREDICTORS	No	No	Yes
Controls	No	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	1,129	1,129	1,129
Pseudo R^2	0.085	0.148	0.200

Panel A regress fraud on the deception score of the roadshow host. Panel B assess the robustness to alternative classifiers, alternative ways of averaging deception scores across managers, and excluding the part of the video with managers' lowering their heads. Panel C excludes the IPO-year fraud cases whose fraud periods are not known to be before the IPO date. We include control variables as listed in Column 2 of Panel B Table 4 in all regressions in Panel B and the last columns of Panel A and C. *OTHER PREDICTORS* include *FSCORE* in Dechow et al. (2011), six financial-statement cues in Bao et al. (2020), *Bao et al. Predictors*, lying word categories in Larcker and Zakolyukina (2012), *LIEWORD*, textual predictors generated by five topics of IPO roadshow transcripts following Brown et al. (2020) and Blankespoor et al. (2023), *RS_TOPICS*, audio-based deception score, *DECEPTION_A_FIRM*, and picture-based fraud predictors facial masculinity following Jia et al. (2014), *FWHR*. All variables are defined in Appendix A. Standard errors are clustered by industry. *Z*-statistics are reported in parentheses. ***, **, * denote significance at 1, 5, and 10 percent levels, respectively.

APPENDIX A. Variable Definitions

Variable	Definition
Dependent Variables	
FRAUD	Indicator variable that equals one if a firm commits at least one financial fraud before or during the IPO year, and zero otherwise. A firm is considered to commit financial fraud if it receives a sanction from the CSCR or the Shenzhen Stock Exchange for financial misbehavior.
$BHAR_{EXPPOST20DAY}$	A firm's buy-and-hold market-adjusted returns over a 20-trading-day window that starts on the IPO lock-up expiration date.
$BHAR_{EXPPOST60DAY}$	A firm's buy-and-hold market-adjusted returns over a 60-trading-day window that starts on the IPO lock-up expiration date.
$BHAR_{EXPPOST120DAY}$	A firm's buy-and-hold market-adjusted returns over a 120-trading-day window that starts on the IPO lock-up expiration date.
$STOCK\_SALES_{EXPPOST10DAY}$	The total amount of managers' stock sales over a 10-trading-day window that starts on the IPO lock-up expiration date and is calculated as the number of stocks sold multiplied by the sold price scaled by the market value (in thousands) at the time lock-up period expires.
$STOCK\_SALES_{EXPPOST20DAY}$	The total amount of managers' stock sales over a 20-trading-day window that starts on the IPO lock-up expiration date and is calculated as the number of stocks sold multiplied by the sold price scaled by the market value (in thousands) at the time lock-up period expires.
$STOCK\_SALES_{EXPPOST60DAY}$	The total amount of managers' stock sales over a 60-trading-day window that starts on the IPO lock-up expiration date and is calculated as the number of stocks sold multiplied by the sold price scaled by the market value (in thousands) at the time lock-up period expires.
Independent Variables	
DECEPTION_V_FIRM	The average value of all executives' machine-based visual deception score in the IPO roadshow video. We normalize it to range between zero and one. See section 3.3 for details.
DECEP_TP1(2/3/4/5)	The sum of all sentences' machine-based visual deception scores multiplied by the sentence's weight of topic1 (2/3/4/5). The sentence's visual deception score is predicted by the trained random forest model using visual features. We normalize it to range between zero and one. See section 3.3 for details.
Control Variables: Other Predictors	
FSCORE	Scaled probability of misstatement, estimated as the predicted probability of misstatement scaled by the unconditional probability of misstatement from Dechow et al. (2011) Table 7, Panel A, model 1. The predicted probability is equal to (e predicted value/ (1 + e predicted value)) where the predicted value = −7.893 + 0.790 × RSST Accruals + 2.518 × Change in receivables + 1.191× Change in inventory + 1.979 × % Soft Assets + 0.171 × Change in Cash Sales − 0.923 × Change in Return on Assets + 1.029 × Actual Issuance. The unconditional probability is 494/ (494 + 132,967) = 0.003701. All input variables for calculating predicted value are winsorized at the 1 percent and 99 percent levels.
LIEWORD	The frequency of the lie words that equals to the difference between the lying words and the truth words listed in Table 6 of Lacker and Zakolyukina (2012) and scaled by the total word counts. Specifically, *LIEWORD* = (References to general knowledge + Extreme positive emotion + Negations + Certainty + Tentative－Anxiety words－Shareholder value－3rd person plural pronouns－Impersonal pronouns) / Total word counts.
DECEPTION_A_FIRM	The average value of all executives' audio deception score (DECEPTION_A) in the IPO roadshow video. DECEPTION_A is constructed by using the same method as DECEPTION_V except using audio features. To extract audio features, we first extract audio files (.wav) from videos and then use Librosa package to extract audio features, including prosodic and spectral features.

Variable	Definition
FWHR	The average value of all executives' facial width-to-height ratio (fWHR) by measuring the distance between cheekbones and the height of the upper face of each executive from each frame in the IPO roadshow video.
Bao et al. Predictors	Six financial-statement cues in Bao et al. (2020), including *CASH, CURRASSET, RETEARN, PAYABLE, INV, EQUITY*. Specifically, *CASH* = (Cash + Short-Term Investments)/Total Asset; *CURRASSET* = Current Asset/Total Asset; *RETEARN* Retained Earnings /Total Asset; *PAYABLE* = Accounting Payable /Total Asset; *INV* = Inventory /Total Asset; *EQUITY* = Equity /Total Asset.
RS_TOPICS	Five variables that measure the topics distribution of roadshow transcripts. The distribution of topic 1 (2/3/4/5) is the percentage of sentences discuss this topic. The topic of a sentence is generated by LDA.
Control Variables	
SIZE	The natural log of 1 plus the firm's total asset in the fiscal year before the IPO year.
ROA	Net income divided by total assets in the fiscal year before the IPO year.
LEV	Total debt divided by total assets in the fiscal year before the IPO year.
VC	Indicator variable that equals one if the firm has venture capital backing at the time of IPO.
DUALITY	Indicator variable that equals one if the chairman and CEO of an IPO firm are the same person at the time of the IPO.
BOARD	The natural log of 1 plus the number of board directors at the time of IPO.
NEG_EMOTION	The mean value of negative emotion subtracting positive emotion for all executives. We calculate the negative emotion for each executive by averaging the negative emotion as it appears per frame (1/10 second) of the video for each executive video. We obtain emotion via Face++ emotion recognition algorithm API. This API categorizes facial emotion into seven dimensions: happiness, neutral, sadness, surprise, anger, disgust, and fear. Following Gong et al. (2019), we classify sadness, fear, and disgust as negative emotions and classify happiness as positive emotions.
TONE_FILE	(Positive words – Negative words)/Total word counts in the firm's IPO prospectus reports. Positive and negative word lists are in the Chinese financial sentiment dictionary (CFSD) constructed by Bian et al. (2021). They construct the CFSD by using a multi-stage filtering procedure based on both algorithms and human judgment and list all words and their English translations in their paper.
RISK_FILE	The percentage of words in the firm's IPO prospectus reports that are in the risk word lists. The risk word list is constructed in the Wingo Textual Analysis Database (www.wingodata.com) by using the method of "seed word + word embedding similar word", see details on the website.
IND	The percentage of independent directors.
GROWTH	Sales growth in the 2 years prior to the IPO year.
LEGAL	Proportion of shares owned by legal entities.
INDIV	Proportion of shares owned by individual stockholders.
FOREIGN	A dummy variable taking the value one (1) if the firm has foreign stockholders.
TOP	The percentage of shares held by the largest stockholder.
TOP10_HHI	The stock ownership of the second through tenth largest owners is recorded as a Herfindahl index.
MARKETINDEX	A comprehensive index compiled by Fan and Wang (2003) that captures the regional market development from the following aspects: (1) relationship between government and markets, such as the role of markets in allocating resources and enterprises' burden in addition to normal taxes; (2) the development of non-state business, such as the ratio of industrial output by private sector to total industrial outputs; (3) development of product markets, such as regional trade barriers; (4) development of factor markets such as FDI and mobility of labor; (5) development of market intermediaries and legal environment such as the protection of property rights.

Variable	Definition
BIG10	An indicator variable that equals one if a firm's auditors is auditors with the 10 highest market shares, and zero otherwise.

APPENDIX B. Principal Components Description

PCA	Name	Top 10 feature loadings
PCA1	Face and Mouth Movement	0.0312*x_4_max+0.031*x_5_max+0.0306*x_6_max+0.0303*x_7_max+0.0302*x_48_max+0.0301*x_60_max+0.03*x_8_max+0.0299*p_tx_max+0.0299*x_59_max+0.0299*x_49_max
PCA2	Nose Movement	0.0501*x_30_min+0.0496*x_29_min+0.0494*x_31_min+0.0493*x_32_min+0.0492*x_66_min+0.0492*x_65_min+0.0492*x_51_min+0.0492*x_57_min+0.0492*x_63_min+0.0492*x_52_min
PCA3	Chin Movement	0.0444*Y_8_percentile50+0.0444*Y_8_median+0.0439*Y_7_percentile50+0.0439*Y_7_median+0.0433*Y_9_percentile50+0.0433*Y_9_median+0.0415*Y_6_median+0.0415*Y_6_percentile50+0.0408*Y_10_percentile50+0.0408*Y_10_median
PCA4	Brow and Gaze Movement	-0.0438*gaze_1_x_max +0.0382*x_1_min +0.0382*x_17_min +0.0381*x_2_min + 0.038*x_18_min +0.0379*x_3_min +0.0379*AU02_c_percentile75 -0.0379*gaze_0_x_max +0.0377*x_0_min +0.0376*x_4_min
PCA5	Mouth and Cheek Movement	-0.0559*AU14_c_percentile25-0.0531*AU14_c_median-0.0531*AU14_c_percentile50-0.0482*AU06_c_median-0.0482*AU06_c_percentile50-0.0472*AU06_c_percentile25-0.0453*AU10_c_percentile75-0.0451*p_0_percentile25-0.0423*AU12_c_percentile75-0.0408*p_0_mean
PCA6	Genuine Smile	0.0726*AU12_c_percentile75+0.06*AU06_c_percentile75+0.0595*AU07_c_percentile50+0.0595*AU07_c_median+0.0573*AU12_c_percentile50+0.0573*AU12_c_median+0.0564*AU07_c_percentile25+0.0561*AU06_c_percentile50+0.0561*AU06_c_median+0.0547*AU07_c_percentile75