Face Value: Do Perceived-Facial Traits Matter for Sell-side Analysts?

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September 30th, 2019

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Abstract

Applying social psychology models and machine learning techniques to the LinkedIn profile pictures of U.S. sell-side analysts, we extract three key perceived facial traits – approachability, attractiveness, and dominance. We show that approachable and dominant analysts have more accurate forecasts, produce longer reports, and the effects are larger for firms with more fundamental uncertainty. In contrast, attractiveness only improves forecast precision for junior analysts and the pre-Reg FD period. While approachable analysts herd with managers, dominant analysts actively participate in conference calls and are less likely to herd. Approachable and attractive analysts are more likely to become all-star analysts. For female analysts, however, dominance is negatively associated with their forecast accuracy and career outcomes.

"The appearance stems from the mind."

--- Guiguzi, Chinese philosopher and educator (475-221 BC)

1. Introduction

Human faces convey a wealth of information critical to social interactions. The ancient art of Physiognomy, which involves reading character traits from facial appearance, was used by philosophers in classical antiquity as early as Aristotle. While one may dismiss Physiognomy as junk science, recent findings in psychology, cognitive science and neuroscience show that our brains automatically compute the social value of faces and use it to make important decisions, and this process is influenced by ones culture, biases and stereotypes.[1] Meanwhile, the proliferation of big data and machine learning techniques have enabled major corporations to increasingly adopt artificial intelligence and face scanning technologies for hiring decisions. Proponent of such practices argue that such use eliminate the human biases, but critiques say that the algorithm is opaque and the use can exacerbate human biases or even create new biases (Harwell, 2019).[2]

This paper attempts to shed light on this debate. Using the latest machine learning techniques, we analyze and quantify the facial perceptions of financial analysis and directly map them into a comprehensive set of outcome variables. Sell-side analysts provides an ideal setting

[1] Hassin and Trope (2000) reported that 75% of surveyed people believe that they can gain useful information about a person's personality from their face. Willis and Todorov (2006) show that experiment subjects make inferences regarding the competence, aggressiveness, and attractiveness of a stranger within 0.1 seconds of exposure to his or her face, as a "fast, intuitive, System 1 processes". The perceived competence of a face is useful in predicting the outcomes in both an experiment setting and real-world elections (Antonakis & Dalgas, 2009; Todorov, Mandisodza, Goren, & Hall, 2005). In wage setting, online-dating, and teaching evaluations, attractive people consistently obtain better outcomes (Hamermesh & Biddle, 1994; Zebrowitz, 1999; Hamermesh and Parker, 2003; Mobius and Rosenblat, 2006; and Finkel et al., 2012). Research in judicial justice has shown that baby-faced individuals are less likely to receive severe judicial outcomes than mature-faced ones (Zebrowitz & McDonald, 1991). See Hugenberg and Wilson, (2013) and Todorov (2017) for a review.

[2] As of October 2019, more than 100 employers, including Hilton and Unilever, now use an AI-driven interview assessment system developed by HireVue, and more than a million job seekers have been analyzed. HireVue's AI-based algorism has not been made public.

for such analysis as communication and social interactions play crucial role in their information acquisition process, in which first impressions can be important. Furthermore, the outcome variables such as information quality, effort, performance and career outcomes are directly measureable. In addition, personal traits such as gender, ethnicity, educational background, industry experience are observable and can be accounted for, allowing the analysis to disentangle the impact of alternative determinants.

We obtain the *Linkedin* profile and pictures of all U.S. sell-side analysts existed in the I/B/E/S database between 1990 and 2017. Following Sutherland et al., (2013) and Vernon et al. (2014), we apply a neural network-based model to the analysts' pictures and extract key perceived facial traits. Sutherland et al., (2013) label the three traits as approachability, youth-attractiveness, and dominance and show that they jointly explain over 75% of the variation in the facial impressions observed by human subjects in an experimental setting.

– approachability, youth-attractiveness, and dominance for 795 sell-side analysts whose profile pictures are available on *Linkedin* as of May 2018. [3]

We confirm the feasibility of applying this model to our subjects by comparing human-rated traits labeled by volunteers on Amazon MTurk versus the facial traits labeled by the neural network model for a random testing sample of 100 analysts. We match the identification of individual analyst using their names and brokerage firm employers with *I/B/E/S* forecasts, the full text of their reports from *Thomson Investext*, and their participation in firms' conference calls from transcripts on *Seeking-Alpha*. Following Clement (1999), Malloy (2005), Green et al. (2014) and

[3]Trained against a large sample of facial pictures rated by human raters, the model developed by Vernon et al. (2014) provides a relatively high accuracy (mean correlation 75.6%) in estimating a person's perceived facial impressions. See section 3.1 for detail. Following Vernon at al. (2014), we focus on three key facial traits – approachability, youth-attractiveness, and dominance, because prior literature (e.g. Sutherland et al., 2013) demonstrate that these three traits are the most important traits to describe facial impressions of people and jointly can explain over 75% of the variation in the facial impressions observed by the perceivers.

Bradley et al. (2017), we use "Proportional Mean Absolute Forecast Error" (PMAFE) as a proxy for the relative accuracy of individual analysts' EPS forecasts.

We find that controlling for other personal characteristics such as experience, age, etc., individual analyst's approachability and dominance are positively associated with their EPS forecast accuracy and the amount of information they provide to the market measured by the total length of their written reports. Next, to explore the possible mechanisms driving these results, we show that analysts' dominance trait is positively associated with the intensity of their public information collection measured using the frequency of the analyst's conference call participation. This evidence suggests that approachability and dominance affect the accuracy of analysts' forecast potentially through different channels: approachable analysts provide more accurate EPS forecasts by collecting more information through private channels, possibly through better connections with the management and industry experts. On the other hand, more dominant analysts provide more accurate EPS forecasts by collecting information more through public channels such as conference calls.

Next, we study the impact of gender and career seniority on the cross-sectional difference of association between facial traits and forecast accuracy. Regressions that separately analyze male and female analysts sample show that the positive association of attractiveness and dominance with forecast accuracy mainly exist in male analysts. In female analyst sample, the result suggests that dominance is negatively associated with accuracy, consistent with the psychology literature that perceived aggressiveness (one key principle component of the dominance trait) causes a more significant disadvantage for female (Heilman, 2012) than for male, due to the conventional belief of gender norms. When partitioning the sample based on analysts' industry seniority, results show that our main finding is mainly attributable to analysts who have been following the industry for more than two years. For junior analysts who have just entered to follow the industry (less than two years), youth-attractiveness is positively associated with her/his forecasts accuracy.

We exploit Reg-FD as a shock to analysts' cost of public and private information acquisition and attempt to identify the channels through which facial traits may affect forecast accuracy. Our results show that the positive associations between forecast accuracy and both approachability and dominance only exist in the post-Reg FD period; in contrast, in the pre-Reg FD period, only analysts' youth-attractiveness is positively associated with EPS forecast accuracy. These findings suggest that in the pre-Reg FD period attractiveness dominates the other two facial traits for sell-side analysts – possibly because attractive analysts could more easily get private information through tipping from management. By curbing such selective disclosure, Reg-FD resulted in a more leveled playing field for sell-side analysts.

Finally, we study the association between sell-side analysts' facial traits and the outcomes of their career – measured by their election to All-Star Analysts by the institutional investors. We find that controlling for other analyst and brokerage level characteristics, approachability, and youth-attractiveness are positively associated with the propensity of becoming all-star analysts, while dominance not significantly related to the career outcomes. Consistent with the survey result of Brown et al. (2015), our evidence suggests that, when evaluated by institutional investors, individual analyst's forecast accuracy is not the only critical factor for evaluating individual sell-side analysts. It is plausible that communication skills and information collection capability associated with the approachability and youth-attractiveness traits of sell-side analysts are also valued by institutional investors.

Our empirical results are robust to a battery of robustness tests, including controlling for facial width to height ratio - fWHR (He et al., 2019), facial traits ranked by gender, and various fixed-effects such as age and brokerage fixed effects.

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Ai can be a tool to be used to learn about a lot of things. The power of AI, aggregating individual ability to assess others, highly correlated with successful outcomes of analysts. In this context, we can quantify inferences and map directly into analyst outcomes. Diff with WTH: WTH more likely to be determined by physical traits (genetic build up, suspect of eugenics), AI captures soft information, attitude, happiness, value. Extract the reduced form of nature+nurture. AI is powerful.

MOVE TO COMPARISON TO LITERATURE

Recent studies in finance examine the relationships between facial traits and capital market outcomes. Some studies examine the direct effect of facial traits. For example, Graham et al. (2016) show that perceived competence is more important than "beauty" in CEO selection and compensations design. Blankespoor et al. (2017) show that the investor's perception of a CEO's capability is associated with IPO pricing. Bai et al. (2019) find that mutual fund managers who appear "confident" outperform their peers. Huang et al. (2019) show that entrepreneurs' look of competence and appearance increase with the likelihood of receiving investment. Another stream of the literature uses facial features as a proxy for testosterone level to study the biological foundation of financial decision making. For example, Jia et al. (2014) find a positive association between male CEO's facial width to height ratio (fWHR) and the propensity of financial misreporting, while He et al. (2019) document that fWHR of Chinese male sell-side analysts is associated with higher forecast accuracy.

This study examines the effects of the facial traits of individual US sell-side analysts on their performance and career development. We use sell-side analysts as the research subject for the following reasons: First, the existing literature mainly focuses on CEOs (Graham et al., 2016; Blankespoor et al., 2017), who work in a different setting and perform a different role than sell-side analysts. Given the different emphasis on skills and work setting, current findings of facial traits of the CEO are unlikely to extend to sell-side analysts. Second, because of the need to market their service, many sell-side analysts voluntarily post their profile pictures on professional social networks such as *LinkedIn*. These profile pictures are usually shot by photographers for professional purposes; therefore, they have high-quality and similar ambient environments such as lighting, backgrounds, and outfits, providing an ideal dataset to study the effect of their facial traits. Third, recent literature in biology provides evidence that the connection between fWHR and male testosterone level is inconclusive (e.g., Bird et al., 2016; Hodges-Simeon et al., 2016; Kosinksi, 2017), our study therefore serves to provide additional evidence regarding the relationship between the facial traits of sell-side analysts and their forecasting ability, and the channel through which the effect takes place.

This study contributes to several steams of literature. First, our results contribute to the literature examining the impact of perceptions of individuals on economic outcomes. Prior studies focus on CEO's facial perceptions, showing an association between CEO's perceived beauty and competence and their compensation and the pricing of the IPO stocks (Graham et al. 2016, Blankspoore et al. 2017). Our study adds to this literature by providing evidence that facial perceptions also affect sell-side analysts' performance and career outcome.

Second, our results contribute to the literature on sell-side analysts, a key group of information intermediaries in capital markets, by providing new evidence of heterogeneity across individual analyst. The existing literature shows that characteristics of individual analyst such as gender, industry experience, location, and cultural background affect their performance. (Kumar, 2010; Bradley et al., 2017; O'brien and Tan, 2015; Malloy, 2005; Gunn, 2013; Merkley et al. 2017). We add to this literature by showing that individual analyst's facial traits affect their forecast accuracy and career outcomes. This study also provides evidence of the channel through which analysts' facial traits affect the performance. Our finding that reg-FD eliminated the privilege of a subset of the analysts who are perceived as more attractive is also new to the literature.

Third, this study contributes to the finance literature by introducing and validating a novel and more cost-effective method to study the effects of the perception of individuals on the capital market. Most prior studies on individual perceptions in finance use human-rated features of individuals; the rating process used in these studies are not only costly and therefore difficult to be extended to large sample studies, but also is subject to human error. To the best of our knowledge, our study is the first in finance to apply a machine-learning-based methodology to reliably extract perceptions from facial pictures for a large sample of individual subjects; our approach can be widely used at relatively low cost.

The rest of the paper is arranged as follows: Part II review related literature and describe our motivations. Part III provides detail descriptions of our data and measurement constructions. Part IV presents the empirical results on the relationship between facial traits and forecast accuracy. Part V presents the empirical results on the relationship between facial traits and analysts' career outcomes. Part VI discusses robustness tests, and Part VII concludes.

2. Related Literature and Motivations

2.1 The impact of facial traits on decision-making

Lavater's *Essays on Physiognomy* described in minute detail on how to relate facial features to personal traits. Since its publication in 1772, the book has been reprinted in more than 150 editions around the world. Despite that some of the descriptions in the book will easily strike most people today as ludicrous, it is now well-established in psychology studies that people make personal inferences from faces after minimal time exposures (Bar, Neta, & Linz, 2006; Todorov, Pakrashi, & Oosterhof, 2009; Willis & Todorov, 2006), and that these inferences predict important social outcomes such as political elections and CEO selections (Flowe & Humphries, 2011; Olivola & Todorov, 2010a; Rezlescu, Duchaine, Olivola, & Chater, 2012; Graham, Harvey, & Puri, 2010; Rule & Ambady, 2008b).

In the study by Antonakis and Dalgas (2009) published in *Science*, 681 Swiss children aged 5 to 13 years participated in a game in which they are required to choose a captain of their boat by looking at pairs of faces of candidates from 57 French parliamentary runoff elections. Without any information other than the faces, the average probability of a child's choosing the actual election winner was 71%, indistinguishable from those adult participants who rated the targets on competence, intelligence, and leadership. Similar results are shown by Todorov et al. (2005) in experiments using the candidates for US Senate and House of Representatives from 2002 to 2004. The fact that children with little experience evaluate leaders in ways similar to adults suggests that the way human beings form perception of faces is not driven by experiential learning but through some automatic mechanism that we gained through evolutions (Antonakis and Eubanks, 2017).[4]

[4] In addition to these evidence, other findings also support the evolution view of facial perceptions. For example,

Facial traits of individuals also play a vitally important role in the business regime. For example, Linke, Saribay, & Kleisner, (2016) show that trustworthy-looking managers tend to occupy higher hierarchical positions in a company. Rule and Ambady (2010, 2011) show that among the managing partners of America's Top 100 law firms, partner's ratings of Power (competence, dominance, and facial maturity) are significantly correlated with the profitability and growth of their firms. Graham, Harvey, and Puri (2016) document that the look of competence is a more important factor than "beauty" in CEO selections and the competent looks are priced into CEO compensation more than attractiveness. Using video clips from the CEO's roadshow presentation before the IPO, Blankespoor et al. (2017) show that investors' perception of the CEO's capability is associated with IPO pricing. These studies mainly focus on the relationship between facial perception of leaders of business such as CEO or managing partners; their finding may not extend to other capital market participants such as the sell-side analysts.

Different from the studies that directly examine the feature of faces, another stream of literature uses facial features such as the facial width-to-height ratio (fWHR) as a proxy of individual's level of testosterone and exam the impact of their associated biological motivation. Studies have shown that fWHR is associated with a wide array of features such as self- and other-perceived aggressiveness, dominance, physical performance, due to its potential link with level of testosterone in male (Lefevre and Lewis., 2013, Carré and McCormick, 2008, Loehr and O'Hara, 2013, Mileva et al., 2014, Tsujimura and Banissy, 2013).

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studies also find that inferences are made in milliseconds (Willis & Todorov, 2006); judgments generalize across cultures (Berggren et al., 2010)— though with some nuances regarding the attributes on which judgments are based (Rule et al., 2010); there is usually strong consensus across raters regarding inferences made (Penton-Voak, Pound, Little, & Perrett, 2006); and individual face-based judgments correlate with activity in particular brain regions (Rule et al., 2011; Todorov, Baron, & Oosterhof, 2008).

Recent studies in accounting show that there is a positive association between male CEO's fWHR and the propensity of financial misreporting and being named perpetrator by the SEC, and one possible explanation is that hormone testosterone influence both aggressive behavior and the shape of the face. (Jia, Lent, and Zeng, 2014). He et al. (2019) document that fWHR of Chinese male sell-side analysts is associated with higher forecast accuracy, due to their achievement drive – a trait predicted by fWHR. Despite the popularity of fWHR, recent findings in biology provided more large-sample evidence questioning the link between the fWHR and the level of the hormone testosterone in the adult male.[5] Given the inconclusive findings on the relationship between fWHR and testosterone, our study also seeks to examine if the perceptions of faces can serve as another possible explanation for the observed relationships between facial structure and the outcomes.

2.2 Literature on Individual Analyst's Characteristics

Sell-side analysts are among the most important information intermediaries in the capital markets. By collecting and analyzing information related to companies' performance, sell-side analysts provides forecasts of companies' EPS and trading recommendations useful to investors' decision making – this usefulness of is evident by the well-documented stock price reactions to analysts' forecast and recommendation revisions (e.g. Womack, 1996, Hong, Lim and Stein, 2000). Earlier studies often treat sell-side analysts as a homogenous group and focus on the consensus (i.e. mean or median) of their forecasts. Recent literature shows that a number of innate characteristics and external factors such as analysts' forecasting experience, political

[5] For example, Bird et al. (2016) find no association between any specifications of testosterone and fWHR in a sample of 1,041 males. Hodges-Simeon et al. (2016) focus on male testosterone in adolescence, a period the fWHR was formed, and find no evidence supporting this association between fWHR and testosterone in adolescence males. Kosinksi (2017) investigate the relationship between 55 well-established psychometric scales and fWHR and find no substantial associations between self-reported characteristics and fWHR.

views, portfolio complexity, the prestige of their brokerage house, and their industry experience are related to analysts' performance (Clement (1999); Gilson et al. (2001); Malloy (2005); Kirk et al. (2014); Jiang, Kumar, and Law (2016), Bradley et al. (2017)).

Using the "level of beauty" of Chinese analysts rated by human raters, Cao et al. (2016) find that the "level of beauty" has a positive impact on analysts' forecast accuracy and the informativeness of stock recommendations, the likelihood of becoming an all-star analyst and hired by bigger brokerage houses. Despite their findings, it is not guaranteed that the same relationship would hold in the US, given the significant institutional and legal differences between these two countries. It remains an empirical question of whether strong legal systems and regulations in the US such as Reg-FD can curb the information advantage of analysts with specific characteristics.

We examine the three principal components of facial traits – approachability, youth-attractiveness, and dominance, following Sutherland et al. (2013).[6] The outcome variables we investigate are their relative forecast accuracy, the length of analysts' reports written, and their career outcomes measured using all-star analyst elections. Ex-ante, it is not known whether these facial traits are related to the performance of sell-side analysts. For example, on the one hand, approachability may enhance analyst's communication skills which will help analyst collect more information, on the other hand, according to a survey by *Institutional Investor* magazine, communication skills are ranked in lower importance by sell-side analysts when compared with analytical skills such as industry knowledge (Bradley et al. 2017). Youth-Attractiveness may help analysts gain personal access to the management and industry experts but may also not

[6] We use the three facial impressions because they have been shown to capture around 73% of the variations in the thirteen attributes commonly used in describing the first impressions of faces. Sutherland et al. (2013)

affect due to the strengthened legal requirement on fair disclosure. Dominance, a factor mainly comprises of confidence, intelligence and health, may hinder the communication skills but may also signal the level of competence of individual analysts.

3. Data and Facial Impression Measures

3.1 Measuring Facial Traits using Machine Learning

Measuring facial traits on large scales is a challenging task. Although studies have shown that human brains can draw trait inferences from the facial appearance of other people within 0.1 seconds of exposure, the process happening inside the brain is largely unobservable to researchers. Studies rely on data rated by human subjects to conduct empirical research. The rating process by human raters is not only costly and therefore difficult to extend to large sample studies, but also involves potential human errors due to the subjectivity of the raters. Recently, the fast development of computer image recognition and artificial intelligence such as machine learning enabled us to analyze the features of human faces and establish the underlying connection between faces and the perceived personality of the subjects by people.

Vernon et al. (2014) developed a machine-learning model to characterize the relationship between physical features of faces and the perception of their social traits measured from three dimensions – Approachability, Youth-Attractiveness, and Dominance.[7] Despite that human beings can draw a variety of facial traits when exposed to a face, these three dimensions have been shown to capture the majority of variance among all popular traits used in previous studies. (Sutherland et al. 2013) [8]. From 1,000 highly variable real-life face photos rated by human

[7] When exposed to a face, human observer is able to form a battery of trait judgements including age, aggressions, trustworthiness, confidence, intelligence, dominance and so on (e.g. Boothroyd et al., 2007; Oosterhof & Todorov, 2008; Walker & Vetter, 2009). To elucidate the underlying dimensions that govern these trait judgements, studies asked participants to infer traits from faces and the applied principal components analysis (PCA), which reduced the trait judgements into fewer dimensions (Oosterhof and Todorov, 2008; Todorov and Oosterhof, 2011).

[8] Using 1,000 face pictures collected from the Internet and rating provided by 50 participants, Sutherland et al. (2013)

raters, Vernon et al. (2014) first define the location of 179 fiducial points such as the outline of eyes and the bottom of the chin (a process known as delineating) with the help of software, and using the coordinates of these fiducial points, they construct measures of physical characteristics of each face such as eyebrow area, nose height, bottom lip curve, skin hue variations. This process is also known as “dimension reduction”, which is essential for image processing and machine learning because it reduces the high-dimensional facial images to 65 measure of physical characteristics, making it possible to use neural networks to establish the connection between faces and perceptions. Next, they adopt a variety of different neural network architectures including simple linear architecture and non-linear architectures with hidden layers to compute the translation between facial features of a face and the perceived traits by human raters. The accuracy of the models is evaluated using an out-of-sample 10-fold cross-validation method.[9] After comparing the correlation between human-rated impression scores and model-rated impression scores predicted by various neural networks, they show that a linear model outperformed other neural network models with considerably high accuracy.[10]

3.2 Data and Measures of Facial Traits

3.2.1 Acquiring Face Photographs of Sell-side Analysts

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shows that the 13 most-commonly used facial traits by previous studies can be reliably captured by three principal factors – approachability, youth-attractiveness, and dominance. These three factors together explained 72.38% of the variance in the original 13 facial traits. In Sutherland et al. (2013), 1,000 (500 male and 500 female) facial images were acquired from the Internet and 50 participants (25 male and 25 female) are asked to rate 13 facial traits using a 1 to 7 scale, including aggression, approachability, trustworthiness, smile, confidence, health, attractiveness, age, babyfacedness, dominance, sexual dimorphism, intelligence, skin. For detailed description of the experiment and PCA factor loadings on the 13 facial traits, please see the appendix.

[9] For this procedure the set of 1,000 faces was divided into 10 subsamples, each containing the physical attributes derived from 100 images together with the corresponding factor scores. For each “fold” one set of 100 image attributes was reserved for use as test cases, and the remaining 900 were used to train and then validate a freshly initialized network. The network was trained to fit the physical measures to the factor scores from the training cases. After training, the predicted factor scores for the reserved 100 untrained faces were computed. The predictions were then set aside and the process repeated until all 1,000 images had been used as test cases.

[10] The average correlations between the network predictions and actual factor scores were $\rho_{approachability} = 0.90$, $\rho_{youthful\text{-}attractiveness} = 0.70$, and $\rho_{dominance} = 0.67$. (all $P < 0.001$)

We download all EPS forecasts made between 1990 to 2017 in I/B/E/S and obtained the last name and first name initials of the analysts from I/B/E/S detailed history recommendation file by matching the identification number of an individual analyst used by I/B/E/S. To obtain analyst's full first name and the brokerage of an individual analyst, we search on Thomson Reuters Investext using the last name of the analyst and the firm she/he follows.[11] Next, we search on LinkedIn using the keywords "first name + last name +brokerage firm", from the returned search results we pick the person that match all three search criteria and carefully review the profile available on LinkedIn including the job title and working experiences to avoid potential identification errors.[12] Profiles pictures of the identified analysts are downloaded from Linkedin.com with the highest resolution option available as of May 2018. Demographic information of individual analyst is also downloaded to be used as control variables. A sample screenshot of the LinkedIn webpage is attached in Figure 1.

Our final sample consists of 795 individual sell-side analysts, the summary statistics reported in Table 1- Panel A provides demographic information: 13% of the analysts are female; the median year they first appear in I/B/E/S is 2004; The detailed sample matching process is reported in Appendix 2. [13]

3.2.2 Image Processing and Facial Traits Modeling

[11] We assign the first name to the amaskcd available on IBES if the following conditions are satisfied: 1) the last name and the first name initial on IBES must match the last name and first name of the author of the PDF reports on Investext. 2) at least one EPS forecast is submitted to IBES for the same company in the window of –365 to +365 days relative to the issuance date of PDF reports.

[12] In less than 0.1% of the searches we conducted, the returned results contain two or more people with exactly the same first/last name and brokerage firms. In this scenario, we look at their profile pictures, job title and working experiences on LinkedIn to determine if they are the same person. If we are not able to confidently identify which one is the person associated with the IBES identification code, all duplicates observations are dropped from our sample.

[13] As reported in Appendix A2, only 22% of all analyst forecasts are issued by an analyst with active LinkedIn accounts. Among the "LinkedIn forecasts", about 48% are issued by analysts with a usable portrait. A comparison between the LinkedIn analysts "with photo" and "without photo" shows that the forecasts accuracy is not significantly different across the two groups.

Following Vernon et al. (2014), we first delineate 68 landmark locations of important fiducial points (such as the tip of the nose, the left edge of the left eye) on a face using an automated facial point annotation tool developed in computer science. This method has been proved to yield accurate facial annotations and has been widely used in face recognition tasks such as mobile payment and security systems (Sagonas et al., 2016).[14] Figure 2-Panel A provides an example of the delineating process we have employed in this study. Also, we obtained HSV (Hue, Saturation, and Value) information related to the color and texture of facial area (enclosed area of the facial annotations) from the API (application programming interface) provided by Scipy module available on Python 3.4 for facial traits modeling.

Next, using the coordinates of these fiducial points annotated in the previous step, and the brightness and color properties of pixels within the facial area enclosed by the fiducial points, we calculated a range of image-based measures summarizing physical characteristics including geometry layover and color and texture of each face. Following Vernon et al. (2014) we calculated 65 measures of the physical attributes of a face, including measures related to the size and shape of the face as a whole (e.g., head width), individual facial features (e.g., bottom lip curvature), their spatial arrangement (e.g., mouth-to-chin distance), the presence/absence of glasses and facial hair, and information about the texture and color of specified regions (e.g., average hue of pixels within polygons defined by fiducial points around the irises). Where applicable, size and area values were first standardized by dividing by a proxy for apparent head size. A list of attributes used in this study and their corresponding calculations are available in Table OA1. An illustration of the attributes extraction is shown in Figure 2- Panel B.

[14] We adopt the "Facial Point Annotation" tool developed by the Intelligent Behavior Understanding Group (i-bug) at the Imperial College. The detailed 68 points mark-up used for our annotations are reported in our appendix. This tool is publicly available for academic research purposes on https://ibug.doc.ic.ac.uk /resources/facial-point-annotations/. The process is illustrated in Figure 2

Vernon et al. (2014) suggest that the among the neural networks they estimated, a linear architecture modeled as a weighted combination of attributes plus a constant (equivalent to multiple linear regression) has outperformed other neural network models that include non-linear layers, and have provided the coefficients estimated for the three predicted facial traits. [15] We then multiply these known coefficients by the 65 facial attributes calculated previously, and the results are our raw measures of the facial traits of the sell-side analysts.[16] The three raw measures are then ranked among all sell-side analysts following firms in the same 2-digit SIC industry in year *t*, and standardized to [0,1], respectively. [17]

Despite that Vernon et al. (2014) have shown a reasonably high accuracy of the linear model in predicting the three facial traits, its applicability in our sample is not automatically guaranteed. For example, the photos we collected are professional photographs of sell-side analysts, and the context may differ from that of the "ambient" pictures collected from the Internet in Vernon et al. (2014). To further confirm the validity of our measurement construction, we randomly selected 100 analysts' profile picture from out sample and hired 10 raters (5 male, 5 female) on Amazon Mechanical Turk to rank these 100 analysts on the three dimensions using a 1 to 7 scale and analyze the Pearson correlations between the model-predicted traits and manually-labeled traits from Amazon Turk raters. The average correlations between the model-predicted impression scores and the manually-labeled scores are $\rho_{\text{approachability}} = 0.92$, $\rho_{\text{youthful-attractiveness}} = 0.75$, $\rho_{\text{dominance}} = 0.72$ (All significant at $p<0.01$ level). These

[15] Vernon et al. (2014) shows that the linear model accounted for a substantial proportion of the variance for all three trait factors (58% on average). The coefficients loadings for 65 facial attributes are provided for academic research on www.pnas.org/cgi/doi/10.1073/pnas.1409860111, Table 1.

[16] Following Vernon et al. (2014), in our empirical analysis, raw values were scaled linearly into the range (−1:1).

[17] We rank these three facial traits within the analysts who follow the same industry to maintain consistency with our dependent variable, which is also a relative measure of forecast accuracy. We apply relative measures of facial traits within the same industry to isolate other possible confounding factors of forecast accuracy that varies across different industries. The standardized facial traits are calculated as $(\text{trait}_{i,t}-\min_t)/(\max_t-\min_t)$

correlations are similar to those used in validity check in Vernon et al. (2014), and confirm that the model performed reasonably well in our sell-side analyst sample.

Figure 2- Panel C provides an intuitive visual summary of the analysts classified using the method described. We sort the individual analyst sample into ten deciles based on the predicted facial impression scores generated by the model and render the average face for each decile by aligning the 68 fiducial points delineated previously and apply Delaunay Triangulation transformation to extract the average color of pixels surrounding similar geometric regions of faces in each decile.[18] Consistent with Oosterhof and Todorov (2008), approachability involves the mouth and the shape of the mouth, which links to smiling expression. Attractiveness mainly involves the eye, in line with the argument of Zebrowitz et al. (2003) that links relatively large eyes to a youthful appearance. Dominance is mainly linked to the structural features which represent a masculine appearance such as eyebrow height and cheek gradient. In our online appendix, we also provide GIF animations of a series of images with incremental changes in each decile across the three facial traits. These animations show that the changes across combinations of features: for example, increased approachability involves an increased smiling expression around the mouth area. [19]

3.3 Measurement of Analyst Forecast Accuracy

We adopt a relative performance measure at the firm-quarter level as our dependent variable in order to better identify the systematic differences in analysts forecast accuracy

[18] A naïve average face will generate a misaligned image since only one center point can be aligned. Here we employ Delaunay triangulation transformation to better align images. Specifically, we first create an empty image with fixed center and coordinates system as our master image. Then, each face is divided into sub-triangles based on 68 previously detected key fiducial landmarks and Delaunay triangulation algorithm. Each triangle in each image is then aligned and wrapped to our master output image accordingly to generate the aligned average face shown in Figure 4.

[19] Those GIF animations are created by ButtonFlow. By employing advanced motion interpolation and motion smoothness algorithms provided by ButterFlow as well as high performance GPUs, we render over 30 intermediate frames for each pair of average faces. The manually added frames gives the perception of a more fluid animation.

because it holds company and time factors constant and offers a cleaner setting to examine the impact of individual-analyst-level characteristics (Clement, 1999). This measure has been widely used in accounting and finance literature to study the impact of individual analyst characteristics on their performance. (e.g., Clement, 1999; Malloy, 2005; De Franco and Zhou, 2009; Green et al., 2014; Bradley et al., 2017).

We calculate proportional mean absolute forecast error ($PMAFE_{i,j,t}$) of analyst *i* for firm *j* at time *t*. Specifically, $PMAFE_{i,j,t}$ is the difference between the absolute forecast error ($AFE_{i,j,t}$) of analyst *i* for firm *j* in time *t* and the mean absolute forecast error of all analysts following firm *j* at time *t*, scaled by the mean absolute forecast error of all analysts following firm *j* at time *t* to reduce heteroskedasticity. To compute PMAFE, we include the full I/B/E/S sample. As constructed, negative values of $PMAFE_{i,j,t}$ represent above-average performance. AFE and PMAFE are calculated as follows:

$$AFE_{ijt} = Absolute\left(Forecasted\ EPS_{ijt} - Actual\ EPS_{ijt}\right)$$

$$MAFE_{jt} = {\textstyle\sum_{i}^{n}} AFE_{ijt} / n$$

$$PMAFE_{ijt} = (AFE_{ijt} - MAFE_{jt})/MAFE_{jt}$$

AFE_{ijt} is the absolute forecast error for analyst *i*'s forecast of firm *j* for year *t*, and $MAFE_{jt}$ is the mean absolute forecast error for firm *j* for year *t* excluding analyst *i*'s forecast. The lower the value of PMAFE, the more accurate the forecast.

4. Sell-side Analysts' Facial Traits and Forecasts Accuracy

4.1 Baseline regression: The Effect of Facial Traits on Forecast Accuracy for Individual Sell-side Analyst

We first use a multivariate OLS regression model to formally test the relationship between the three facial traits estimated previously and the accuracy of their EPS forecasts by estimating the following model with industry fixed effects and year fixed effects; standard errors are heteroskedasticity-consistent and double-clustered at the industry and year level:

$$
\begin{aligned}
PMAFE_{i,j,k,t} = {} & \beta_0 + \beta_1 \times Facial\,Traits + \beta_2 \times No\,Following\, + \beta_3 \times DTop10 \\
& + \beta_4 \times DSIC2 + \beta_5 \times DGExp + \beta_6 \times DFExp + \beta_7 \times DHorizon + \beta_8 \times DAge \\
& + \beta_9 \times DPortfolio\,Size + \beta_{10} \times Size + \beta_{11} \times BM + \beta_{12} \times Past\,Return \\
& + \varepsilon \qquad (1)
\end{aligned}
$$

We include a group of control variables that could affect the earnings predictability of individual analyst such as analyst ability and experiences, brokerage size, analyst busyness, and job complexity, and firms' information environment. Following Clement (1999), all control variables at individual-auditor-level are mean-adjusted by minus the mean of value for all analysts following firm *j* at time t. First, to control for individual-analyst-level ability and experience, we include the general experience (GEXP) as the total number of years that analyst *i* appeared in I/B/E/S, the firm-specific experience (FEXP) as the total number of years since analyst *i* first provide a forecast related to firm *j*, the age of analyst (AGE) calculated from the graduation year from Bachelor's degree reported on LinkedIn profile, and whether analyst *i* is from one of the Top 10 brokerage houses (TOP10). Second, we control for analyst portfolio size and job complexity, by including the total portfolio size measured by the number of firms followed by analyst *i* at time *t* (PORTFOLIO) and the number of 2-digit SIC industries followed by analyst *i* at time *t*. Third, we include a control variable that proxies for the time from analyst *i*'s forecast to the date of firms' earnings announcements (HORIZON). Last, we control for a group of firm characteristics that related to their information environment including the number of analysts following (FOLLOWING), size, book-to-market ratio and last quarter's buy-and-hold abnormal returns.

Table 3 reports the regression results. Each model in table 3 includes 190,600 earnings forecasts made by sell-side analysts. Model 1 and model 3 shows that the approachability trait and dominance trait of sell-side analysts significantly decrease the relative forecast errors of the forecasts they issued. In terms of economic magnitude, on average an analyst whose approachability trait ranked top among those following the same industry *(approachability=1)* is 3.02% more accurate *(t = 3.96)* than an analyst who ranked bottom *(approachability=0);* an analyst whose dominance trait ranked top among those following the same industry *(Dominance =1)* is 2.18% *(t= 2.70)* more accurate than an analyst who ranked bottom *(Dominance =0)*. In model 2 we did not find a significant correlation between the youth-attractiveness trait of individual analyst and the relative forecast accuracy, in contrast to findings of Cao et al. (2016) using a sample of Chinese analysts.

4.2 Are the Effects of Facial Traits Different for Male vs. Female Analysts?

Next, we explore whether the effect of facial traits on individual sell-side analysts' forecast accuracy is different across gender. Despite female analysts account for a minority of our sample (12.6%), the forecasts they issued on averages are more accurate than that of the male analysts.[20] We run the same regression from our baseline test separately among male and female analysts and reports the result in Table 4-Panel B. Column 1 to 3 in Table 5 suggests that the effects of approachability and dominance on forecast accuracy we find previously are mainly attributable to male analysts. For female analysts, the approachability trait does not seem to affect their forecast accuracy; this is likely because female analysts already appear much more approachable compared to male analysts.[21] In Table 4-Panel A, we show that approachability

[20] In Table 4- Panel A, we show that PMAFE (female) = -0.0434 while PMAFE (male) = -0.0140, suggesting that compared to their peers following the same firm, on average a forecast made by female analysts in our sample is 4.34% more accurate while forecast made by male analysts in our sample is only 1.40% more accurate than the peer analysts.

[21] In the main test, we did not separately rank the traits of male and female analysts. This is because in the original human rating process both male and female samples are used by the machine learning program to identify the three facial traits. However, in our robustness check reported in the online appendix Table OA2, we separately rank analysts by gender and find that our results remain unchanged.

(female) has a mean of 0.6291 while approachability (male) has a mean of 0.2843, the difference is statistically significant at $p<0.01$ level. The result also suggests that dominance trait is negatively affecting the forecast accuracy for female analysts. This finding is consistent with the psychology literature that perceived aggressiveness (one key principle component of the dominance trait) causes a more significant disadvantage for female (e.g. Heilman, 2012) than for male, due to the conventional belief of gender norms.

4.3 Are the Effects of Facial Traits Different for Junior vs. Senior analysts?

It is interesting to test if the relationship between facial traits and the forecast accuracy varies along the sell-side analysts' career stage. This question speaks to the source of facial traits: are facial traits mainly capturing short-term perception or innate personal characteristics. If facials traits are purely capturing spontaneous perceptions, as the analysts' working experiences increases, the effect of facials traits on forecast accuracy will become weakened because perceptions are gradually substituted by alternative channels such as increased personal relationships. To test this conjecture, we use an indicator variable I_{JUNIOR} to indicate if a forecast is made by an individual analyst in her/his first two years of following a specific industry.[22] We estiamte our main model with an interaction term of I_{JUNIOR} with the measures of facial traits to capture the effect of industry juniority. Results are reported in Table 5. The interaction term between youth-attractiveness and I_{JUNIOR} is negative and significant at 5% level, suggesting that youth-attractiveness has a positive impact on forecast accuracy when the analyst has just entered to follow an industry. The interaction terms on approachability and dominance are not significant, suggesting that the impact of these two traits does not vary significantly with the length of analysts' industry experience.

[22] Results are robust if include the first three years of her/his experience.

These evidences, taken together, suggest that youth-attractiveness affect analysts' performance when they are junior, consistent with findings that beauty signals capability and facilitates communications (Mobius and Rosenblat, 2006, Andreoni and Petrie, 2008), however the impact of beauty seems temporary and decay over the longer term as an analyst gains experience and social connections. On the other hand, we do not observe a significant difference in approachability and dominance, suggesting that these two traits are relatively more innate and may capture personal characteristics crucial for sell-side analysts.

4.4 Are the Effects of Facial Traits Different Pre and Post Regulation Fair Disclosure?

Given the baseline regression results, we are interested in exploring the channels through which these facial traits of sell-side analysts affect the accuracy of their forecasts. Regulation Fair Disclosure (Reg-FD) prohibits firms' selective disclosure of information to a subset of analysts. Literature documented that Reg-FD has leveled the playing field among sell-side analysts by curbing passage of private information from managers to analysts. For example, Cohen et al. (2010) find that analysts with school ties to senior managers at covered firms perform better than non-connected analysts, but only in the pre-Reg FD period. Tang (2013) shows that after Reg-FD, buy-side analysts earn a less excessive return when investing in the stocks they used to follow as a sell-side analyst, due to the decrease in private information dissemination from managers to analysts. We hypothesize that if certain facial traits of analyst affect their forecast accuracy by facilitating the communication of private information from the company executives, this effect should be weakened in the post-Reg FD period.

We partition the sample into pre-Reg FD and post-Reg FD period based on the revision date of each EPS forecast and estimate the same regression model in our baseline result.[23] The

[23] We use the adoption date of Reg FD – October 23, 2000 as the cut-off date for post-Reg FD observations.

regression results in Table 6 suggest that the correlations we found in our full sample mainly exist in the post-Reg FD period, however in the pre-Reg FD period the youth-attractiveness of sell-side analysts positively affect the forecast accuracy. Specifically, in the pre-Reg FD period, forecasts issued by an analyst that ranked the highest in youth-attractiveness among all analysts following the same industry *(attractiveness=1)* is on average 3.75% more accurate *(t=1.67)* than analyst who ranked the lowest *(attractiveness=0)*. The coefficients for youth-approachability and dominance are not statistically significant in the pre-Reg FD period but are statistically and economically significant in the post-Reg FD period.

These findings suggest that attractiveness trait of sell-side analysts helps them gain access to private information from firms' management in the pre-Reg FD period, and the privilege of selective disclosure from the management has crowded out the impact of approachability and dominance on forecast accuracy.[24]

4.5 Facial Traits and the Amount of Information Provided by Individual Sell-side Analyst

We hypothesize two (non-exclusive) channels through which facial traits affect the performance of individual sell-side analysts: First, certain facial traits such as youth-attractiveness and approachability could facilitate analysts' communications with market participants such as firm management, industry experts, and other peer analysts. As a result, the information collected from the social network of the analysts will help them make more accurate forecasts. Second, facials traits such as dominance may proxy for superior ability in analyzing information because dominance mainly comprises of traits such as confidence, intelligence, and dominance.

[24] The impact of youth-attractiveness on forecast accuracy in the pre-Reg FD period is similar to findings in Cao et al. (2016) using a sample of Chinese analysts. These evidences together suggest that under weak legal environment, attractive (described as beautiful in Cao et al) analysts have superior access to private information from the management.

We use the following model to analyze an alternative measure of analysts' performance – the amount of information they provide to the market measured by the length of analysts report they write:

$$LENGTH_{i,j,k,t} = \beta_0 + \beta_1 \times Facial\ Traits + \beta_2 \times No\ Following\ + \beta_3 \times DTop10 + \beta_4 \times DSIC2 + \beta_5 \times DGExp + \beta_6 \times DFExp + \beta_7 \times DHorizon + \beta_8 \times DAge\ + \beta_9 \times DPortfolio\ Size + \beta_{10} \times Size + \beta_{11} \times BM + \beta_{12} \times Past\ Return + \varepsilon \quad (2)$$

where LENGTH is the natural logarithm of the number of pages contained in an analyst pdf report after removing duplicated content such as the disclaimer, legal notice, and brokerage information, etc. To control for potential confounding factors of report length, we include a battery of control variables of firm characteristics and forecast characteristics, and firm, brokerage, year-quarter fixed effects.

Results reported in Table 6 suggest that reports written by analysts ranked top in approachability *(approachability =1)* among those following the same industry on average is 9.2% longer than the reports written by analysts ranked bottom *(approachability =0).* Also, reports written by analysts ranked top in dominance *(dominance=1)* among those following the same industry on average is 24.4% longer than the reports written by analysts ranked bottom *(dominance=0).* These results suggest that analysts who have high approachability and dominance traits generate more information supply to the capital markets.

4.6 Facial Traits and the Information Acquisition Activities of Individual Sell-side Analyst

This section tests whether analysts' facial traits affect their information acquisition activities by examining the correlation between analysts' facial traits and the frequency of conference call participation. The conference call is an important public information disclosure channel of the company and a valuable opportunity for analysts to publicly access the management. Analysts who are allowed to ask questions during the conference call receive valuable public signals that could be used to complement their existing private information

(Mayew 2008). If analysts' facial traits help them better access the management, we should observe a difference in conference call participation across these facial traits.

We estimate the following regression model:

$$
\begin{aligned}
Log(1 + Num\ of.CC)_{i,t} \\
&= \beta_0 + \beta_1 \times Facial\ Traits + \beta_3 \times Average\ PMAFE + \beta_4 \times No\ of\ forecasts \\
&+ \beta_5 \times Porfolio\ Size + \beta_6 \times Total\ Firm\ Size + \beta_7 \times Average\ BM \\
&+ \beta_8 \times Top10 + \beta_9 \times Age \\
&+ \varepsilon
\end{aligned} \tag{3}
$$

The dependent variable is the natural logarithm of one plus the number of conference calls individual analyst *i* has participated during year *t*. Analyst *i* is considered to have participated in a conference call if she/he is allowed to ask at least one question to the management. We collect conference call transcripts for around 270,000 conference calls from Seeking-Alpha that happened between 2000 to 2017 and matched with our individual analyst sample by searching for their full first and last name, and the brokerage they were affiliated at the time of the conference call. We estimate the model using 5,188 analyst years in our sample, controlling for other factors of the analyst such as the portfolio size, performance, and prestige.

The result in Table 8 shows that the dominance trait of the sell-side analysts is positively affecting the frequency of conference call participation. In terms of economic significance, analysts with high dominance traits participate in an average of 13.84% more conference calls (equals to 0.36 conference calls) than analysts with low dominance traits in a year. This finding suggests that sell-side analysts' dominance traits increase the propensity of public information collection activities. Because dominance traits mainly reflect confidence, competence, and dominance feature of the human faces, it is likely that analysts with dominance traits are perceived by management as more capable and prestigious compared to the peers and as a result are given more opportunities to ask questions during conference calls.

5. Sell-side Analysts' Facial Traits and Career Development

5.1 Facial Traits and the Probability of Winning the All-Star Elections

Every year, the *Institutional Investor* magazine organize the all-star analyst election among thousands of institutional investors such as asset managers and buy-side analysts. Being elected all-star analyst marks a successful career outcome for the sell-side analyst as it brings significant increases in coverage, clients and compensation (Groysberg et al. 2011). Whether the facial traits of sell-side analyst affect the probability of being elected all-star analysts is an important research question for both academia and practice. We collect all-star analyst list from *Institutional Investor* magazine from 1991 to July 2015 and match with our individual analyst sample using the full name and brokerage name.

We estimate a logistic regression model to explore the likelihood of becoming an all-star analyst for analyst *i* in year *t*, controlling for analyst characteristics such as lagged all-star, average forecast accuracy, portfolio size, the prestige of the brokerage, etc. We include year fixed effect and use heteroskedasticity-robust t-statistics clustered at the individual analyst level. To further control for reverse causality, all control variables are included using their 1-year lagged values. The logistic model is stated as follow:

$$\begin{aligned}(All\ Star = 1)_{i,t} &\\ = \beta_0 + \beta_1 \times Facial\ Traits_{t-1} + \beta_2 \times Lag(All\ Star)_{t-1} + \beta_3 \times Portfoilo\ Size_{t-1} &\\ + \beta_4 \times SIC2_{t-1} + \beta_5 \times Brokerage\ Size_{t-1} + \beta_6 \times Average\ PMAFE_{t-1} &\\ + \beta_7 \times Total\ Firm\ Size_{t-1} + \beta_8 \times Age_{t-1} + Year\ Fixed\ Effect &\\ + \ \varepsilon & \qquad (4)\end{aligned}$$

Column 1 in Table 9 suggests that analysts with high approachability trait are more likely to be elected all-star analyst compared to analysts with low approachability trait. The odds ratio is 1.64, suggesting that the odds of electing all-star analysts for analysts ranked top in approachability trait (*App=1*) is 64% higher than those ranked bottom (*App =0*) among all analysts following the same industry-year. Column 2 in Table 9 suggests that *ceteris paribus*, analysts with higher youth-attractiveness trait are more likely to be elected all-star analyst compared to analysts with lower youth-attractiveness trait. The odds ratio is 1.96, suggesting that the odds of electing all-star analysts for analysts ranked top in the youth-attractiveness trait (*Yo-At =1*) is 96% higher than those ranked bottom (*Yo-AT=0*) among all analysts following the same industry-year. These findings suggest that analysts' approachability and youth-attractiveness traits increase their probability of being elected all-star analysts by institutional investors.

5.2 Facial Traits and the Probability of Winning the All-Star Elections: Male vs. Female Analysts

We repeat Model 4 in female and male analysts sample separately and report the result in Table 10. Approachability is insignificant after we partition the full sample based on gender, suggesting that the positive coefficients we show in section 5.1 are mainly attributable to cross-gender variation in approachability. [25] Youth-attractiveness trait is positive and significant at the 0.01 level in the female sample but not significant in the male sample. This finding suggests that youth-attractiveness is an important factor for institutional investors' vote of all-star analysts in female analysts, but not an important factor when voting for male analysts. We also find that dominance is negatively associated with all-star election outcomes for female analysts, but positively associated with all-star election outcomes for male analysts. This finding conforms to the previous result in forecast accuracy of female and male analysts, it suggests that institutional investors' voting decision is also affected by the "gender norms"- i.e. perceived aggressiveness (one key principle component of the dominance trait) causes a disadvantage for female (Heilman, 2012) due to the conventional gender norms.

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[25] Table 4-Panel A shows that the mean *APP* for male is 0.5630 and 0.6291 for female.

6. Additional Analysis

6.1 When do Facial Traits Matter More? The Impact of Firms' Earnings Volatility

Following Thomas (2002) and Dichev and Tang (2009), we use firms' idiosyncratic earnings volatility as a measure of firm-level information asymmetry. We expect that when information asymmetry is high, analysts' facial traits have a greater impact on their forecast accuracy because the information-collecting ability becomes more valuable. We partition our full sample based on earnings volatility, measured as the standard deviation of seasonal earning changes estimated over the four-year period ending on the fiscal-end date, and estimate the main regression in both samples. Our result in Table 11 suggests that approachability trait decrease forecast error in the high earnings volatility group, but not in the low earnings volatility groups; consistent with the conjecture that approachability is an important determinant of individual analysts' information acquisition ability. Dominance is significant in both high/low volatility groups, and the coefficients are not statistically significant, suggesting that dominance has more emphasize on reflecting individual analyst's capability.

6.2 Facial Traits and the Propensity of Herding to Management Earnings Guidance

As a further identification of the channel through which facial traits are associated with the forecast accuracy when test whether analysts with certain facial traits are likely to herd to management earnings guidance. We define the dependent variable as an indicator variable *Herd* that equals to one if an analyst's EPS forecast is within one cent distance from the preceding management forecast. We use a logit regression with control variables including analyst-level, brokerage-level, and firm-level. The results in Table 12 suggest that analyst's approachability trait increases their propensity of herding to management forecasts, while dominance traits decrease their propensity. This result suggests approachability analysts are more credulous when making their forecasts, while dominant analyst forms their forecasts more independently.

7. Robustness Tests

7.1 Controlling for Facial Width-to-Height Ration (fWHR)

Given recent studies using facial width-to-height ratio (fWHR) as a proxy for level of testosterone of male analysts, which is related to risk-taking and motivation drive (He et al. 2019), a legitimate concern with our analysis is that the relationship between our measure of facial traits and analysts' performance is driven by fWHR. As a robustness check, we first explore the correlation of fWHR to the three measures of facial traits we derived following Vernon et al. (2014), and include fWHR as an additional control variable to our baseline regressions. We measure fWHR following Lefevre, et al. (2013) as the distance between the left and right zygion relative to the distance between the upper lip and the highest point of the eyelids, these points are previously annotated using the land-mark delineating tool introduced in Section 3.

Correlations of fWHR and our three measures of facial traits are reported in Table R1, fWHR is significantly correlated with the three measures of facial traits at $p<0.05$ level. However, the correlation coefficients are all statistically small (with the maximum correlation = -0.1008). Next, we include fWHR as an additional control variable into our baseline regression of Model (1) and Table R2 suggests that our regression results are unchanged.

7.2 Ethnicity Fixed Effect

Literature in the social science domain finds that ethnicity is associated with the effectiveness of communication in settings such as the classroom (Collier and Powell, 1990) and clinics (Johnson et al., 2004). It is possible that analyst's ethnicity is an underlying driver of both analysts' facial traits and their forecast accuracy. To address this concern, we identify the ethnicity of each sell-side analyst by inferring from their last names using Python module Ethnicolr, which utilizes US census data to predict and ethnicity-based on last name. [26] Each analyst is categorized into *nh_white* (non-Hispanic white), *asian* (Asian), *nb_black* (non-Hispanic black) or *hispanic* (Hispanic). We include an ethnicity-fixed effect and redo our baseline regression of forecast accuracy and all-star elections. Results are reported in Table A4. Both sign and significance of our original results remain unchanged.

7.3 Including Orthogonal Transformed Facial Traits

Because the three facial traits we extracted are correlated with each other, including all three into one regression will raise the concern of multicollinearity. In this robustness test, we include orthogonalized variables for each of the three traits.[27] The process of orthogonalization allows us to transform the three facial traits variables into a set of traits that span the same three-dimensional subspace but are uncorrelated with each other. Our Table A5 results, which shows qualitatively similar results from our baseline regression, suggest that despite the substantial joint common influence caused by high correlation among the facial traits measures, both approachability and dominance trait still retains a unique feature of power or influence that is not captured by the other correlated facial traits dimensions.

7.4 Impact of Reg FD - Balanced window and Cohort Sample Analysis

Our original test of the impact of Reg FD partition the full sample into pre- and post-Reg FD periods, which totally span 28 years (1990-2018). In this robustness test we restrict a shorter

[26] Available at https://ethnicolr.readthedocs.io.

[27] Orthogonalization is achieved via the modified Gram–Schmidt process (Golub and VanLoan, 1996) where our three independent centrality variables are transformed into a mutually orthogonal set of transformed facial traits variables that span the same three-dimensional subspace as the original trait factors. We use the following orthogonalization order from first to last: approachability-attractiveness-dominance. Alternative ordering lead to similar results.

window of -5 to +5 years of Regulation FD (1995-2005) to rule out the possibility that our results may be confounded by other events. Results in Table A6-Panel A are similar to that of Table 6. To further rule the possibility that the different impacts of facials traits on forecast accuracy pre and post Reg-FD is due to the turnover in analyst industry caused by Reg-FD (i.e. analysts in the pre- and post Reg-FD periods are not the same group of analysts and therefore are not directly comparable), we conduct a robustness test on a cohort sample in the shorter window.[28] Results in Table A6- Panel B shows similar results to our main test, despite minor discrepancy in the level of significance on *dominance*, possibly due to lack of power caused by shredded sample size.[29]

7.5 The Impact of Re-Touched Portraits

We are concerned that some portrait photos we collected on LinkedIn may be re-touched using photo-editing software such as Adobe Photoshop. If this is the case our measurement of facial traits using machine learning may subject to measurement errors because these re-touched photos may not truthfully reflect the facial geometries of the analyst. We used a recent technology developed in computer vision to identify retouched photos (Wang et al. 2019). [30]Overall, the mean probability of photo retouching in our sample is low at less than 1%. Still we eliminated 12 analysts whose photo are suspicious of re-touching (with re-touching probability > 10%) and find that our original results (Table A7) are robust.

[28] The cohort sample is restricted to a constant sample requiring analyst appearing in IBES in both pre and post periods within [-5, 5] years range of Reg-FD.

[29] Y*outh-attractiveness* remains negative and significant, consistent to the main test in the pre Reg-FD period; *approachability* remains negative and significant, *dominance* become insignificant. *Dominance* is negative and significant in the main test, but is not significant in the robustness test despite same sign. This is possibly due to lack of testing power cased by a significantly reduced sample size (18% of the original sample).

[30] Each image is analyzed by a deep machine learning model proposed and open-sourced by Wang et al. (2019). Codes, models and related paper is available at Github repo at https://github.com/PeterWang512/FALdetector. The output of the machine learning model is a float number between 0 and 1 indicating the probability the input image is being photoshopped. Images with photoshopped probability greater than or equal to 10% are dropped from this estimation sample. In all, 2516 observations issued by 12 analysts are eliminated.

7.6 Brokerage Fixed Effect and Age Fixed Effect – OA2 Panel B

There is a concern that brokerage houses may have preference over the facial traits of the analysts it hires, as a consequence the observed relationship between analysts' facial traits and their performance is largely dominated by brokerage characteristics and not individual analyst facial traits. To check the robustness of our result, we add a brokerage dummy to our baseline regression in Table R4. Because our youth-attractiveness is negatively correlated with age (Table 2), and age not only reflect the experience but also other psychological preferences such as risk-taking, we also include age fixed effect as a robustness check in Table R5. Results from Table R4 and Table R5 suggest that our baseline results are robust.

7.7 Gender-Adjusted Facial Traits – OA2 Panel A

Because female and male analysts naturally demonstrate different facial traits, for example, female analysts on average appear more approachable and have higher youth-attractiveness compared to male-analysts. (see Appendix 3 for detail), one concern we have is that the impact of facial traits on analysts' performance is largely attributable to gender difference. To check the robustness, we separately rank each of the three facial traits within female/male analysts and re-run our baseline regression. Table R3 suggest that our results are robust to the alternative ranking within gender.

8. Conclusions

Using a machine-learning model, we extract measures of facial traits from LinkedIn profile pictures of 795 US sell-side analysts. We first show that the approachability trait and dominance trait of sell-side analysts are positively associated with their forecast accuracy. However, these positive effects only exist in the post-Reg FD period and are dominated by the youth-attractiveness trait in the pre-Reg FD period, suggesting that youth-attractiveness is associated with private information acquisition from the management in the pre-Reg FD period. We also find that youth-attractiveness is positively associated with forecast accuracy for junior analysts, potentially because the perception of youth-attractiveness is a transitory advantage for junior analysts and may decay over the longer-term career. Additionally, the positive effects of attractiveness trait and dominance traits on forecast accuracy mainly attribute to male analysts. For female analysts, dominance negatively affects their forecast accuracy, suggesting potential discrimination against feminism in the sell-side analyst industry.

Besides forecast accuracy, we also show that analysts' approachability trait and dominance trait positively affect the length of the analyst reports written, suggesting both traits increase the amount of information provided to the market. Also, dominance trait of analysts increases the frequency of conference call participation, consistent with increased public information acquisition activities. We also show that approachability trait and youth-attractiveness trait significantly increase individual analyst's probability of winning the all-star election by institutional investors. Our results are robust to various fixed effects and alternative explanations. Our findings suggest that facial traits play an important role in analysts' forecast accuracy and career development.

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Table 1: Summary Statistics

This table provides the summary statistics of main variables. *APP Raw Score* is the raw approachability score; *YO_AT Raw Score* is the raw youthfulness and attractiveness score; *DOM Raw Score* is the raw dominance score; *APP Raw Score – Male* is the raw approachability score in male group; *YO_AT Raw Score – Male* is the raw youthfulness and attractiveness score in male group, *DOM Raw Score – Male* is the raw dominance score in male group, *APP Raw Score – Female* is the raw approachability score in female group; *YO_AT Raw Score – Female* is the raw youthfulness and attractiveness score in female group; *DOM Raw Score – Female* is the raw dominance score in female group; I_{FEMALE} is a dummy variable taking 1 if an analyst is male and 0 if is female; I_{STAR} is a dummy variable taking 1 if an analyst is elected as All-Star analyst; *NO_FORECAST* is the number of forecasts an analyst issues in a year; *CALL* is the natural logarithm of 1 plus the number of conference calls an analyst participates; *APP* is the ordinal ranking of approachability score at industry-year level; *YO_AT* is the ordinal ranking of youthfulness and attractive score at industry year level; *DOM* is the ordinal ranking of dominance score at industry year level; *PMAFE* is the proportional mean absolute error; *BROKER_SIZE* is the number of unique analysts a brokerage has in a year; *NO_FOLLOWING* is the number of firms an analyst follows in a year; I_{JUNIOR} is a dummy variable taking 1 if an analyst is within her first two years following an industry; $I_{|AMF-AF|}$ is a dummy variable taking 1 if the absolute value of the difference between analyst forecasts and management guidance is less than equal to 1 cent; *PAGE* is the natural logarithm of the number of pages of analyst reports an analyst writes in a year; *DSIC2* is the number of two-digit SICs followed by analyst *i* at time *t* (*SIC2*) minus the average number of two-digit SICs followed by all I/B/E/S/analysts following firm *j* at time *t; DGEXP* is the total number of years that analyst *i* appeared in I/B/E/S (*GEXP*) minus the average tenure of all I/B/E/S/ analysts supplying earnings forecasts for firm *j* at time *t*; *DFEXP* is the total number of years since analyst's *i* first earnings forecast for firm *j* (*FEXP*) minus the average number of years of all I/B/E/S analysts supply earnings forecasts for firm *j* at time *t*; *DHORIZON* is the age of analyst's *i* forecast (*HORIZON*) minus the average age of forecasts issued by all I/B/E/S/ analysts following firm *j* at time *t*; *DAGE* is the age of analyst *i* in year *t* minus the mean analysts' age following the same two-digits SICs in year *t*; *DPORTFOILIOSIZE* is the number of firms followed by analyst *i* for firm *j* at time *t* minus the average number of firms followed by all I/B/E/S/ analysts supplying earnings forecasts for firm *j* at time *t*; *SIZE* is the natural log of market capitalization (*ME*) of the covered firm (in $ millions) by the end of the month prior to the earnings forecast; *ME* is the market capitalization of the covered firm (in $ millions) at the end of the month prior to the earnings forecast; *BM* is the Book value of equity in the fiscal year prior to the earnings forecast divided by the current market value of equity; RET_{6m} is the CRSP value-weighted index-adjusted buy-and hold abnormal return over the six months prior to the announcement date of the earnings forecast.

Panel A: Individual Analyst Level Characteristics

Variables	N	Mean	SD	P25	Median	P75	Skewness	Kurtosis
Individual General Characteristics								
APP Raw Score	795	0.2083	0.3353	-0.0595	0.2556	0.4633	-0.1760	2.3246
YO_AT Raw Score	795	0.0552	0.2574	-0.1041	0.0506	0.2164	0.0043	3.2647
DOM Raw Score	795	0.1597	0.2356	0.0268	0.1697	0.3157	-0.3768	3.3269
APP Raw Score – Male	694	0.1956	0.3294	-0.0620	0.2439	0.4407	-0.1687	2.3934
YO_AT Raw Score – Male	694	0.0332	0.2459	-0.1249	0.0294	0.1840	-0.0450	3.3887
DOM Raw Score – Male	694	0.1817	0.2249	0.0560	0.1936	0.3303	-0.4290	3.6370
APP Raw Score – Female	101	0.2962	0.3634	-0.0331	0.3951	0.5913	-0.3678	2.0395
YO_AT Raw Score – Female	101	0.2084	0.2835	-0.0029	0.2359	0.3901	-0.3157	2.9600
DOM Raw Score – Female	101	0.0074	0.2521	-0.1610	-0.0029	0.1577	0.2470	2.9702
I_{FEMALE}	795	0.1259	0.3320	0.0000	0.0000	0.0000	2.2547	6.0840
Analyst Year Characteristics								

I_{STAR}	5712	0.0769	0.2664	0.0000	0.0000	0.0000	1.9549	4.8216
NO_FORECASTS	5712	2.6863	1.0917	2.0000	3.0000	3.0000	0.0361	2.3390
CALL	5188	2.5908	1.5523	1.3863	3.0910	3.8712	0.5924	1.9529
Analyst Industry Year Characteristics								
APP	19763	0.5419	0.2921	0.2903	0.5385	0.8000	-0.0129	1.8081
YO_AT	19763	0.5419	0.2921	0.2903	0.5385	0.8000	-0.0129	1.8081
DOM	19763	0.5419	0.2921	0.2903	0.5385	0.8000	-0.0129	1.8081

Panel B: Forecast Level Characteristics

Variables	N	Mean	SD	P25	Median	P75	Skewness	Kurtosis
Forecast Characteristics								
PMAFE	190600	-0.0174	0.6743	-0.4255	-0.0526	0.2444	1.2569	5.9656
BROKER_SIZE	190600	15.4270	11.4143	6.0000	13.0000	23.0000	0.7202	2.6144
NO_FOLLOWING	190600	4.4680	3.1687	2.0000	4.0000	6.0000	1.1404	3.9926
I_{JUNIOR}	190600	0.2651	0.4414	0.0000	0.0000	1.0000	1.0643	2.1327
$I_{\lvert MF\text{-}AF \rvert}$	47096	0.5936	0.4912	0.0000	1.0000	1.0000	-0.3790	1.1437
PAGE	24668	1.8732	0.7117	1.6094	1.9459	2.3026	-0.4771	4.1091
Relative Characteristics								
DSIC2	190600	0.0143	1.2244	-0.5000	0.0000	0.5000	0.7154	7.7352
DTOP10	190600	0.0013	0.1888	0.0000	0.0000	0.0000	2.4360	13.1508
DGEXP	190600	-0.0010	4.3287	-2.5038	0.0000	2.1196	0.3103	3.8540
DFEXP	190600	-0.0361	2.5909	-1.1082	0.0000	0.7545	0.5781	6.5584
DAGE	190600	-0.0938	6.7699	-4.0000	0.0000	3.2500	0.3836	4.0945
DHORIZON	190600	-0.3755	31.3757	-15.1250	0.0000	10.1000	0.5456	5.8394
DPORTFOLIO_SIZE	190600	0.0577	8.7285	-4.4000	0.0000	3.6667	1.2491	12.5926
Firm Characteristics								
SIZE	190600	14.7857	1.6628	13.5980	14.8082	16.0583	-0.1990	2.4342
BM	190600	0.5347	0.9900	0.2186	0.3849	0.6401	1.6510	6.1934
RET_{6M}	190600	-0.0122	0.2827	-0.1638	-0.0274	0.1110	1.3704	9.3627

Table 2: Correlation Table
Panel A: Pearson Correlation Table at Forecast Level
This table provides the pairwise Pearson correlation matrix for all characteristics at forecast level. * indicates significance at 5% level.

	PMAFE	*APP*	*YO_AT*	*DOM*	*I_{FEMALE}*	*BROKERSIZE*	*NO FOLLOWING*	*DSIC2*
APP	-0.0099*							
YO_AT	-0.0037	0.0898*						
DOM	-0.0062*	-0.0461*	-0.4958*					
I_{FEMALE}	-0.0140*	0.1374*	0.2209*	-0.1991*				
BROKERSIZE	0.0076*	-0.0067*	0.0868*	0.0090*	0.0127*			
NO FOLLOWING	0.0008	-0.0163*	0.0132*	-0.0045*	0.0379*	0.1082*		
DSIC2	0.0122*	-0.0013	0.0221*	-0.0485*	-0.0148*	-0.0453*	0.0104*	
DTOP10	-0.0022	-0.0056*	0.0513*	-0.0052*	-0.0238*	0.1193*	0.0192*	-0.0166*
DGEXP	0.0060*	-0.0144*	-0.1166*	0.0583*	0.0018	-0.0250*	-0.0227*	0.0588*
DFEXP	-0.0053*	0.0029	-0.0404*	0.0201*	-0.0092*	-0.0421*	-0.0170*	0.0425*
DAGE	0.0065*	-0.0266*	-0.0410*	0.1079*	0.0073*	-0.0412*	0.0025	0.0449*
DHORIZON	0.1328*	0.0039	-0.0184*	0.0032	-0.0018	-0.0230*	0.0027	0.0097*
DPORFOLIO	-0.0010	-0.0204*	0.0282*	-0.0433*	-0.0539*	0.0598*	0.0005	0.4952*
SIZE	0.0038	-0.0094*	0.0242*	0.0309*	-0.0012	0.2135*	0.5496*	0.0033
BM	0.0011	0.0003	-0.0108*	0.0126*	-0.0134*	0.0008	-0.0805*	0.0036
RET_{6M}	0.0058*	-0.0031	-0.0018	-0.0041	-0.0118*	0.0021	-0.0030	0.0020

	DTOP10	*DGEXP*	*DFEXP*	*DAGE*	*DHORIZON*	*DPORTFOLIO*	*SIZE*	*BM*
DGEXP	-0.0671*							
DFEXP	-0.0215*	0.4974*						
DAGE	-0.0379*	0.3469*	0.2363*					
DHORIZON	-0.0149*	0.0127*	-0.0006	-0.0028				
DPORFOLIO	0.0095*	0.2151*	0.1341*	0.0664*	-0.0098*			
SIZE	0.0060*	-0.0032	-0.0098*	0.0117*	-0.0036	0.0197*		
BM	-0.0022	0.0113*	0.0060*	-0.0200*	-0.0021	0.0075*	-0.1900*	
RET_{6M}	0.0036	-0.0002	0.0033	0.0037	0.0019	0.0040	0.0832*	-0.1294*

Panel B: Spearman Correlation Table at Forecast Level
This table provides the pairwise Spearman correlation matrix for all characteristics at forecast level. * indicates significance at 5% level.

	PMAFE	*APP*	*YO_AT*	*DOM*	I_{FEMALE}	*BROKERSIZE*	*NO FOLLOWING*	*DSIC2*
APP	-0.0064*							
YO_AT	-0.0064*	0.0893*						
DOM	-0.0056*	-0.0448*	-0.4955*					
I_{FEMALE}	-0.0137*	0.1362*	0.2221*	-0.1970*				
BROKERSIZE	0.0021	0.0059*	0.0813*	0.0039	0.0150*			
NO FOLLOWING	-0.0192*	-0.0084*	0.0117*	-0.0011	0.0399*	0.1583*		
DSIC2	0.0101*	-0.0006	0.0070*	-0.0359*	-0.0170*	-0.0339*	-0.0413*	
DTOP10	0.0053*	-0.0060*	0.0299*	0.0025	-0.0236*	0.0333*	-0.2131*	0.0054*
DGEXP	0.0093*	-0.0152*	-0.1112*	0.0587*	-0.0054*	-0.0191*	-0.0459*	0.0815*
DFEXP	-0.0030	0.0027	-0.0296*	0.0137*	-0.0023	-0.0414*	-0.0518*	0.0709*
DAGE	0.0061*	-0.0309*	-0.0433*	0.1009*	0.0230*	-0.0403*	-0.0434*	0.0377*
DHORIZON	0.1004*	0.0045*	-0.0219*	0.0058*	-0.0015	-0.0250*	-0.0282*	0.0120*
DPORFOLIO	-0.0002	0.0154*	-0.0127*	-0.0126*	-0.0469*	0.0760*	-0.0299*	0.4632*
SIZE	-0.0091*	-0.0064*	0.0239*	0.0302*	-0.0013	0.2178*	0.5864*	-0.0238*
BM	0.0005	-0.0077*	-0.0166*	0.0241*	-0.0327*	-0.0163*	-0.1420*	0.0121*
RET_{6M}	0.0138*	0.0003	-0.0060*	-0.0030	-0.0217*	0.0125*	0.0276*	0.0004

	DTOP10	*DGEXP*	*DFEXP*	*DAGE*	*DHORIZON*	*DPORTFOLIO*	*SIZE*	*BM*
DGEXP	-0.0462*							
DFEXP	-0.0059*	0.4577*						
DAGE	-0.0164*	0.3401*	0.2256*					
DHORIZON	-0.0100*	0.0180*	0.0033	0.0009				
DPORFOLIO	0.0108*	0.2471*	0.1691*	0.1040*	0.0007			
SIZE	-0.1402*	-0.0204*	-0.0419*	-0.0158*	-0.0170*	-0.0016		
BM	0.0467*	0.0192*	0.0127*	-0.0380*	-0.0087*	0.0159*	-0.2531*	
RET_{6M}	-0.0049*	-0.0025	0.0002	0.0036	0.0035	0.0046*	0.1278*	-0.2126*

Panel C: Pearson Correlation Table at Analyst-Year Level

This table provides the pairwise Pearson correlation matrix for all characteristics at analyst-year level. * indicates significance at 5% level.

	STAR	*APP*	*YO_AT*	*DOM*	*MEAN ERROR*	*NO FORECAST*	*TOTAL SIZE*	*MEAN BM*
APP	0.0316*							
YO_AT	0.0438*	0.1071*						
DOM	0.0036	-0.0871*	-0.4465*					
MEAN ERROR	-0.0261*	0.0085	-0.0094	-0.0187				
NO FORECAST	0.0929*	-0.0186	-0.0038	0.0213	-0.0429*			
TOTAL SIZE	0.1180*	-0.0277*	-0.0056	0.0226	-0.0394*	0.9410*		
MEAN BM	-0.0211	-0.0077	0.0004	0.0042	0.0025	-0.0118	-0.0472*	
NO BROKERAGE	-0.0198	-0.0140	0.0164	0.0312*	0.0186	0.0296*	0.0661*	-0.0161

Panel D: Spearman Correlation Table at Analyst-Year Level

This table provides the pairwise Spearman correlation matrix for all characteristics at analyst-year level. * indicates significance at 5% level.

	STAR	*APP*	*YO_AT*	*DOM*	*MEAN ERROR*	*NO FORECAST*	*TOTAL SIZE*	*MEAN BM*
APP	0.0311*							
YO_AT	0.0352*	0.1059*						
DOM	0.0450*	-0.0878*	-0.4456*					
MEAN ERROR	-0.0118	0.0138	-0.0106	-0.0142				
NO FORECAST	0.1095*	-0.0200	-0.0205	0.0179	0.0074			
TOTAL SIZE	0.1361*	-0.0295*	-0.0153	0.0186	-0.0004	0.9345*		
MEAN BM	-0.0040	0.0139	-0.0369*	0.0610*	0.0244	0.0381*	-0.0316*	
NO BROKERAGE	-0.0364*	-0.0297*	-0.0061	0.0443*	0.0037	0.0412*	0.0824*	-0.0376*

Table 3: Baseline Regression - Facial Traits and Forecast Accuracy

This table reports the OLS regression estimates of analyst facial traits on analyst forecast accuracy. The dependent variable is proportional mean absolute forecast error (*PMAFE*) calculated as the difference between the absolute forecast error for analyst *i* on firm *j* at time *t* and mean absolute forecast error for firm *j* at time *t* scaled by the mean absolute forecast error for firm *j* at time *t*. The facial traits (*APP*, *YO_AT*, and *DOM*) are derived by calculating the ordinal ranking among all analysts following the same two-digits *SICs* at year *t*, adjusted by the total number of analysts following the same industry and year to standardize to [0,1]. Column (1) to (3) reports the estimation results by including each of three facial traits. All continuous variables are winsorized at 1% and 99 % level to avoid the extreme effects of outliers. All estimations have controlled year and industry fixed effects; standard errors are estimated by two-way clustering at firm and analyst level with t-statistics presented in parentheses. All coefficients are multiplied by 100. ***, **, * denotes for significance at the 1%, 5% and 10% level, respectively.

	(1)	**(2)**	**(3)**
APP	-3.0197***		
	(-3.96)		
YO_AT		0.2107	
		(0.26)	
DOM			-2.1813***
			(-2.70)
NO_FOLLOWING	-0.0052	-0.0018	0.0011
	(-0.05)	(-0.02)	(0.01)
DTOP10	0.3213	0.3505	0.3550
	(0.32)	(0.35)	(0.36)
DGEXP	0.1204**	0.1231**	0.1270**
	(2.12)	(2.11)	(2.22)
DFEXP	-0.2598**	-0.2686***	-0.2730***
	(-2.57)	(-2.65)	(-2.70)
DAGE	0.0736**	0.0768**	0.0868**
	(2.14)	(2.24)	(2.55)
DHORIZON	0.2859***	0.2858***	0.2859***
	(43.16)	(43.12)	(43.15)
DSIC2	0.8029***	0.7897***	0.7735***
	(3.85)	(3.77)	(3.68)
DPORTFOLIO_SIZE	-0.0654**	-0.0625**	-0.0652**
	(-2.49)	(-2.39)	(-2.49)
SIZE	-0.1304	-0.1256	-0.1137
	(-0.83)	(-0.80)	(-0.72)
BM	0.1313	0.1307	0.1419
	(0.98)	(0.98)	(1.05)
RET_{6M}	1.1163**	1.1182**	1.1164**
	(1.99)	(1.99)	(1.99)
Intercept	YES	YES	YES
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
Adjusted R2	0.0226	0.0224	0.0225
N	190600	190600	190600

Table 4: Facial Traits and Forecast Accuracy- the Role of Gender

This table analyzes facial treats and forecast accuracy by gender. Panel A provides the grouped T-test result for forecast level characteristics between female and male analysts. Panel B reports the OLS regression estimates of analyst facial traits on analyst forecast accuracy with sample partitioned by analysts' gender. The dependent variable is proportional mean absolute forecast error (*PMAFE*) calculated as the difference between the absolute forecast error for analyst *i* on firm *j* at time *t* and mean absolute forecast error for firm *j* at time *t* scaled by the mean absolute forecast error for firm *j* at time *t*. The facial traits (*APP*, *YO_AT*, and *DOM*) are derived by calculating the ordinal ranking among all analysts following the same two-digits *SICs* at year *t*, adjusted by the total number of analysts following the same industry and year to standardize to [0,1]. Column (1) to (3) reports the estimation results for sample of forecasts issued by male analysts; Column (4) to (6) reports the estimation results for sample of forecasts issued by female analysts. All continuous variables are winsorized at 1% and 99 % level to avoid the extreme effects of outliers. All estimations have controlled year and 4 digits SIC industry fixed effects; standard errors are estimated by two-way clustering at firm and analyst level with t-statistics presented in parentheses. All coefficients are multiplied by 100. ***, **, * denotes for significance at the 1%, 5% and 10% level, respectively.

Panel A: Summary Statistics

Variables	**Male**	**Std.**	**Female**	**Std.**	**Diff. (Male – Female)**
PMAFE	-0.0140	0.6758	-0.0434	0.6621	0.0294***
APP	0.5045	0.2843	0.6291	0.3155	-0.1246***
YO_AT	0.5014	0.2863	0.7035	0.2866	-0.2021***
DOM	0.5630	0.2850	0.3815	0.2982	0.1815***
NO_FOLLOWING	4.4244	3.1509	4.7984	3.2816	-0.3740***
DTOP10	0.0030	0.1897	-0.0111	0.1811	0.0140***
DGEXP	-0.0038	4.3528	0.0207	4.1419	-0.0245
DFEXP	-0.0275	2.5977	-0.1020	2.5377	0.0745***
DHORIZON	-0.3546	31.3444	-0.5343	31.6126	0.1798
DAGE	-0.1118	6.7935	0.0426	6.5867	-0.1544***
DSIC2	0.0209	1.2188	-0.0357	1.2652	0.0566***
DPORTFOLIO_SIZE	0.2285	8.9092	-1.2389	7.0786	1.4675***
SIZE	14.7864	1.6656	14.7802	1.6419	0.0062
BM	0.5396	1.0115	0.4981	0.8081	0.0414***
RET_{6M}	-0.0109	0.2797	-0.0214	0.3044	0.0104***
Observations	**168404**		**22196**		

Panel B: Regression Analysis

	Male			**Female**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
APP	-2.9288***			-2.3590		
	(-3.47)			(-0.99)		
YO_AT		-0.1510			2.5191	
		(-0.17)			(0.96)	
DOM			-2.7849***			5.3745**
			(-3.06)			(1.99)
NO_FOLLOWING	0.0112	0.0126	0.0171	0.0640	0.0804	0.0894
	(0.11)	(0.12)	(0.16)	(0.27)	(0.34)	(0.38)
DTOP10	0.5927	0.5537	0.4858	-0.8212	-0.4115	-0.4159
	(0.55)	(0.51)	(0.45)	(-0.29)	(-0.15)	(-0.15)

DGEXP	0.1210*	0.1221*	0.1287**	0.3068*	0.2704	0.3203*
	(1.96)	(1.93)	(2.07)	(1.66)	(1.46)	(1.72)
DFEXP	-0.2567**	-0.2632**	-0.2675**	-0.1421	-0.1395	-0.1235
	(-2.32)	(-2.37)	(-2.42)	(-0.59)	(-0.58)	(-0.51)
DAGE	0.0939**	0.0990***	0.1115***	-0.2343**	-0.2149*	-0.3262***
	(2.50)	(2.66)	(3.01)	(-1.99)	(-1.80)	(-2.65)
DHORIZON	0.2826***	0.2823***	0.2823***	0.3040***	0.3041***	0.3033***
	(39.75)	(39.69)	(39.73)	(16.22)	(16.23)	(16.20)
DSIC2	0.8395***	0.8398***	0.8214***	0.9552*	0.9229	0.9219
	(3.71)	(3.71)	(3.60)	(1.65)	(1.58)	(1.58)
DPORTFOLIO_SIZE	-0.0809***	-0.0778***	-0.0823***	-0.1008	-0.1165	-0.0867
	(-2.93)	(-2.82)	(-2.99)	(-0.94)	(-1.09)	(-0.81)
SIZE	-0.1491	-0.1377	-0.1208	-0.2302	-0.2638	-0.2248
	(-0.88)	(-0.82)	(-0.72)	(-0.49)	(-0.57)	(-0.48)
BM	0.1495	0.1494	0.1653	-0.3530	-0.3765	-0.3414
	(1.10)	(1.10)	(1.20)	(-0.64)	(-0.67)	(-0.62)
RET_{6M}	1.1384*	1.1399*	1.1300*	0.7562	0.7705	0.8096
	(1.89)	(1.89)	(1.87)	(0.49)	(0.49)	(0.52)
Intercept	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Adjusted R2	0.0225	0.0223	0.0225	0.0435	0.0435	0.0437
N	168404	168404	168404	22196	22196	22196

Table 5: Facial Traits on Forecast Accuracy – The Role of Industry Experience

This table reports the OLS regression estimates of analyst facial traits on analyst forecast accuracy by interacting facial traits with industry experience dummy indicator (I_{JUNIOR}), which is coded as 1 if analyst *i* is in her first two years following industry *k*. The dependent variable is proportional mean absolute forecast error (*PMAFE*) calculated as the difference between the absolute forecast error for analyst *i* on firm *j* at time *t* and mean absolute forecast error for firm *j* at time *t* scaled by the mean absolute forecast error for firm *j* at time *t*. The facial traits (*APP*, *YO_AT*, and *DOM*) are derived by calculating the ordinal ranking among all analysts following the same two-digits *SICs* at year *t*, adjusted by the total number of analysts following the same industry and year to standardize to [0,1]. Column (1) to (3) reports the estimation results by including each of three facial traits. All continuous variables are winsorized at 1% and 99 % level to avoid the extreme effects of outliers. All estimations have controlled year and 4 digits SIC industry fixed effects; standard errors are estimated by two-way clustering at firm and analyst level with t-statistics presented in parentheses. All coefficients are multiplied by 100. ***, **, * denotes for significance at the 1%, 5% and 10% level, respectively.

	(1)	(2)	(3)
APP	-3.1752***		
	(-3.42)		
YO_AT		0.9216	
		(0.94)	
DOM			-2.7133***
			(-2.74)
APP * I_{JUNIOR}	0.3355		
	(0.23)		
YO_AT * I_{JUNIOR}		-3.0204**	
		(-1.96)	
DOM * I_{JUNIOR}			2.2594
			(1.47)
I_{JUNIOR}	1.1935	2.9444***	0.0415
	(1.31)	(3.08)	(0.04)
NO_FOLLOWING	-0.0113	-0.0073	-0.0057
	(-0.12)	(-0.08)	(-0.06)
DTOP10	0.3404	0.3422	0.3628
	(0.34)	(0.34)	(0.36)
DGEXP	0.1452**	0.1506**	0.1500***
	(2.55)	(2.57)	(2.61)
DFEXP	-0.2260**	-0.2382**	-0.2414**
	(-2.21)	(-2.32)	(-2.36)
DAGE	0.0825**	0.0831**	0.0930***
	(2.39)	(2.40)	(2.72)
DHORIZON	0.2860***	0.2859***	0.2860***
	(43.17)	(43.14)	(43.17)
DSIC2	0.7886***	0.7710***	0.7622***
	(3.79)	(3.68)	(3.63)
DPORTFOLIO_SIZE	-0.0572**	-0.0545**	-0.0575**
	(-2.17)	(-2.07)	(-2.19)
SIZE	-0.1052	-0.1019	-0.0896
	(-0.67)	(-0.65)	(-0.57)
BM	0.1406	0.1390	0.1519
	(1.05)	(1.03)	(1.12)
RET_{6M}	1.1168**	1.1272**	1.1139**

	(1.99)	(2.01)	(1.98)
Intercept	YES	YES	YES
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
Adjusted R2	0.0226	0.0225	0.0226
N	190600	190600	190600

Table 6: Facial Traits and Forecast Accuracy - The Impact of Reg-FD

This table reports the OLS regression estimates of analyst facial traits on analyst forecast accuracy by splitting the overall sample into pre and post Reg-TD periods. The dependent variable is proportional mean absolute forecast error (*PMAFE*) calculated as the difference between the absolute forecast error for analyst *i* on firm *j* at time *t* and mean absolute forecast error for firm *j* at time *t* scaled by the mean absolute forecast error for firm *j* at time *t*. The facial traits (*APP*, *YO_AT*, and *DOM*) are derived by calculating the ordinal ranking among all analysts following the same two-digits *SICs* at year *t*, adjusted by the total number of analysts following the same industry and year to standardize to [0,1]. Column (1) to (3) reports the estimation results for overall sample; Column (4) to (6) reports the estimation results for pre-Reg-FD sample and Column (7) to (9) reports the estimation results for post Reg-FD period. All continuous variables are winsorized at 1% and 99 % level to avoid the extreme effects of outliers. All estimations have controlled year and 4 digits SIC industry fixed effects; standard errors are estimated by two-way clustering at firm and analyst level with t-statistics presented in parentheses. All coefficients are multiplied by 100. ***, **, * denotes for significance at the 1%, 5% and 10% level, respectively.

	Overall Sample (1990 - 2018)			**Pre Reg-FD (1990 - 2000)**			**Post Reg-FD (2000 - 2018)**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
APP	-3.0197***			-2.0093			-2.8496***		
	(-3.96)			(-0.88)			(-3.43)		
YO_AT		0.2107			-3.7475*			0.4605	
		(0.26)			(-1.67)			(0.53)	
DOM			-2.1813***			0.3966			-2.3218***
			(-2.70)			(0.16)			(-2.68)
NO_FOLLOWING	-0.0052	-0.0018	0.0011	-0.2904	-0.3033	-0.2867	0.0089	0.0121	0.0143
	(-0.05)	(-0.02)	(0.01)	(-0.53)	(-0.55)	(-0.52)	(0.09)	(0.12)	(0.14)
DTOP10	0.3213	0.3505	0.3550	-2.7630	-2.3527	-2.6240	0.4659	0.4590	0.4751
	(0.32)	(0.35)	(0.36)	(-0.66)	(-0.56)	(-0.62)	(0.45)	(0.45)	(0.46)
DGEXP	0.1204**	0.1231**	0.1270**	-1.0593**	-1.0936**	-1.0401**	0.1273**	0.1307**	0.1320**
	(2.12)	(2.11)	(2.22)	(-2.16)	(-2.22)	(-2.11)	(2.21)	(2.21)	(2.28)
DFEXP	-0.2598**	-0.2686***	-0.2730***	0.6640	0.6766	0.6747	-0.2750***	-0.2846***	-0.2880***
	(-2.57)	(-2.65)	(-2.70)	(1.12)	(1.15)	(1.14)	(-2.68)	(-2.77)	(-2.80)
DAGE	0.0736**	0.0768**	0.0868**	0.0501	0.0408	0.0385	0.0790**	0.0836**	0.0953***
	(2.14)	(2.24)	(2.55)	(0.37)	(0.31)	(0.29)	(2.21)	(2.36)	(2.72)
DHORIZON	0.2859***	0.2858***	0.2859***	0.4391***	0.4385***	0.4392***	0.2757***	0.2756***	0.2756***
	(43.16)	(43.12)	(43.15)	(15.45)	(15.44)	(15.44)	(40.53)	(40.50)	(40.54)
DSIC2	0.8029***	0.7897***	0.7735***	2.0725***	2.1561***	2.1018***	0.7251***	0.7093***	0.6911***
	(3.85)	(3.77)	(3.68)	(2.78)	(2.90)	(2.83)	(3.35)	(3.27)	(3.16)
DPORTFOLIO_SIZE	-0.0654**	-0.0625**	-0.0652**	-0.1590	-0.1670	-0.1681	-0.0616**	-0.0584**	-0.0601**
	(-2.49)	(-2.39)	(-2.49)	(-1.36)	(-1.45)	(-1.43)	(-2.28)	(-2.16)	(-2.23)
SIZE	-0.1304	-0.1256	-0.1137	-0.4031	-0.3540	-0.3879	-0.1344	-0.1335	-0.1188
	(-0.83)	(-0.80)	(-0.72)	(-0.93)	(-0.81)	(-0.89)	(-0.78)	(-0.78)	(-0.69)
BM	0.1313	0.1307	0.1419	-0.5981	-0.5443	-0.5873	0.1923	0.1905	0.2034

	(0.98)	(0.98)	(1.05)	(-0.89)	(-0.82)	(-0.88)	(1.46)	(1.43)	(1.52)
RET_{6M}	1.1163**	1.1182**	1.1164**	1.4062	1.3904	1.4014	0.9786	0.9811	0.9839
	(1.99)	(1.99)	(1.99)	(0.94)	(0.93)	(0.93)	(1.61)	(1.61)	(1.62)
Intercept	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adjusted R2	0.0226	0.0224	0.0225	0.0495	0.0496	0.0495	0.0222	0.0221	0.0222
N	190600	190600	190600	17907	17907	17907	172693	172693	172693

Table 7: Facial Traits and Analyst Report Page Counts

This table reports the OLS regression estimates of analyst facial traits on analyst report length differences. The dependent variable, *PAGE,* is measured by taking the natural logarithm of the number of pages an analyst report contains. The facial traits (*APP*, *YO_AT*, and *DOM*) are derived by calculating the ordinal ranking among all analysts following the same two-digits *SIC* at year *t*, adjusted by the total number of analysts following the same industry and year to standardize to [0,1]. Column (1) to (3) reports the estimation results by including each of three facial traits. All continuous variables are winsorized at 1% and 99 % level to avoid the extreme effects of outliers. All estimations have controlled firm, brokerage, year and quarter fixed effects; robust standard errors are reported with t-statistics presented in parentheses. ***, **, * denotes for significance at the 1%, 5% and 10% level, respectively.

	(1)	(2)	(3)
APP	0.0922***		
	(3.94)		
YO_AT		0.0107	
		(0.45)	
DOM			0.2441***
			(10.49)
NO_FOLLOWING	0.0131***	0.0126***	0.0134***
	(6.04)	(5.84)	(6.21)
DTOP10	-0.0222	-0.0227	-0.0290
	(-0.82)	(-0.84)	(-1.07)
DGEXP	-0.0018	-0.0011	-0.0008
	(-1.09)	(-0.71)	(-0.52)
DFEXP	-0.0118***	-0.0118***	-0.0109***
	(-6.29)	(-6.24)	(-5.84)
DHORIZON	-0.0013***	-0.0012***	-0.0012***
	(-9.88)	(-9.82)	(-9.80)
DSIC2	0.0079	0.0085*	0.0087*
	(1.58)	(1.70)	(1.76)
DPORTFOLIO_SIZE	-0.0026***	-0.0028***	-0.0031***
	(-3.17)	(-3.45)	(-3.79)
SIZE	0.0356***	0.0360***	0.0337**
	(2.62)	(2.65)	(2.48)
BM	0.0672***	0.0645***	0.0631***
	(2.85)	(2.75)	(2.70)
RET_{6M}	0.0045	0.0031	0.0010
	(0.21)	(0.14)	(0.05)
Intercept	YES	YES	YES
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
Quarter FE	YES	YES	YES
Brokerage FE	YES	YES	YES
Adjusted R2	0.4692	0.4688	0.4720
N	24668	24668	24668

Table 8: Facial Traits and Conference Calls Participation Frequency

This table reports the OLS regression estimates of analyst facial traits on conference call participations. The dependent variable for estimation (1) to (3) is the natural logarithm of one plus the number of conference calls analyst *i* participated in year *t (CALL)*. The facial traits (*APP*, *YO_AT*, and *DOM*) are derived by calculating the ordinal ranking among all analysts following the same two-digits *SIC* at year *t*, adjusted by the total number of analysts following the same industry and year to standardize to [0,1]. For consistence, we use analyst *i*'s facial traits in the industry with highest number of forecasts issued in year *t* when merging with annually updated conference calls participation data. All continuous variables are winsorized at 1% and 99 % level to avoid the extreme effects of outliers. All estimations have controlled year and 4 digits SIC industry fixed effects; robust standard errors are reported with t-statistics presented in parentheses. ***, **, * denotes for significance at the 1%, 5% and 10% level, respectively.

	(1)	(2)	(3)
APP	0.0345		
	(0.85)		
YO_AT		-0.0024	
		(-0.06)	
DOM			0.1384***
			(3.12)
MEAN_ERROR	-0.0650*	-0.0649*	-0.0601*
	(-1.89)	(-1.88)	(-1.73)
NO_FORECASTS	0.1238*	0.1281*	0.1410**
	(1.84)	(1.93)	(2.14)
PORTFOLIO_SIZE	0.0272***	0.0272***	0.0277***
	(5.17)	(5.11)	(5.35)
TOTAL_SIZE	-0.0021	-0.0024	-0.0036
	(-0.45)	(-0.53)	(-0.80)
MEAN_BM	-0.0147	-0.0152	-0.0168
	(-0.77)	(-0.80)	(-0.84)
TOP10	0.2191**	0.2188**	0.2054**
	(2.47)	(2.49)	(2.23)
AGE	0.0042	0.0040	0.0023
	(0.80)	(0.76)	(0.45)
Intercept	YES	YES	YES
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
Adjusted R2	0.4508	0.4503	0.4576
N	5188	5188	5188

Table 9: Facial Traits and All-Star Analyst Election Outcome

This table reports the Logit regression estimates of analyst facial traits on star analyst. The dependent variable is a dummy variable taking 1 if analyst *i* is voted as star analyst in *t+1* and takes 0 otherwise. The facial traits (*APP*, *YO_AT*, and *DOM*) are derived by calculating the ordinal ranking among all analysts following the same two-digits *SIC* at year *t*, adjusted by the total number of analysts following the same industry and year to standardize to [0,1]. All continuous variables are winsorized at 1% and 99 % level to avoid the extreme effects of outliers. All estimations have controlled year and industry fixed effects; robust standard errors are reported with t-statistics presented in parentheses. ***, **, * denotes for significance at the 1%, 5% and 10% level, respectively.

	(1)	(2)	(3)
APP	0.4470**		
	(1.98)		
YO_AT		0.7058***	
		(3.02)	
DOM			-0.1008
			(-0.44)
LAG_STAR	3.7179***	3.7361***	3.7194***
	(21.34)	(21.53)	(21.31)
SIC2	0.0056	0.0065	0.0062
	(1.39)	(1.64)	(1.54)
PORTFOLIO_SIZE	0.0181***	0.0196***	0.0188***
	(3.01)	(3.30)	(3.15)
BROKER_SIZE	0.0433***	0.0434***	0.0434***
	(6.55)	(6.64)	(6.63)
MEAN_ERROR	-0.0440	-0.0506	-0.0470
	(-0.32)	(-0.37)	(-0.34)
TOTAL_SIZE	0.0048	0.0045	0.0042
	(1.16)	(1.09)	(1.04)
AGE	-0.0076	-0.0055	-0.0072
	(-1.02)	(-0.72)	(-0.95)
Intercept	YES	YES	YES
Year FE	YES	YES	YES
Pseudo R2	0.4702	0.4719	0.4689
N	5713	5713	5713

Table 10: Facial Traits and All-Star Analyst Election Outcome - Male Analysts vs. Female Analysts
This table reports the Logit regression estimates of analyst facial traits on star analyst with sample partitioned by gender. The dependent variable is a dummy variable taking 1 if analyst *i* is voted as star analyst in *t+1* and takes 0 otherwise. The facial traits (*APP*, *YO_AT*, and *DOM*) are derived by calculating the ordinal ranking among all analysts following the same two-digits *SIC* at year *t*, adjusted by the total number of analysts following the same industry and year to standardize to [0,1]. All continuous variables are winsorized at 1% and 99 % level to avoid the extreme effects of outliers. All estimations have controlled year and industry fixed effects; robust standard errors are reported with t-statistics presented in parentheses. ***, **, * denotes for significance at the 1%, 5% and 10% level, respectively.

	Female			**Male**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
APP	0.3308			0.2806		
	(0.67)			(1.08)		
YO_AT		2.4655***			0.3703	
		(2.99)			(1.42)	
DOM			-2.4966***			0.5016*
			(-4.02)			(1.83)
LAG_STAR	3.7347***	4.0060***	4.0963***	3.8765***	3.8854***	3.8637***
	(8.10)	(8.26)	(8.29)	(19.07)	(19.17)	(19.04)
SIC2	0.0266**	0.0190*	0.0158	-0.0003	0.0009	0.0004
	(2.56)	(1.86)	(1.52)	(-0.07)	(0.20)	(0.08)
PORTFOLIO_SIZE	-0.0106	-0.0094	-0.0162	0.0208***	0.0218***	0.0216***
	(-0.64)	(-0.59)	(-0.94)	(3.19)	(3.35)	(3.30)
BROKER_SIZE	0.0132	0.0216	0.0233	0.0449***	0.0452***	0.0447***
	(0.72)	(1.20)	(1.28)	(5.87)	(5.95)	(5.78)
MEAN_ERROR	0.3830	0.4424	0.4548	-0.2598	-0.2663*	-0.2585
	(1.21)	(1.44)	(1.50)	(-1.63)	(-1.67)	(-1.62)
TOTAL_SIZE	0.0126	0.0110	0.0150	0.0037	0.0036	0.0039
	(1.27)	(1.11)	(1.51)	(0.86)	(0.82)	(0.89)
AGE	0.0714***	0.0702***	0.0843***	-0.0208**	-0.0192**	-0.0208**
	(3.21)	(3.16)	(3.63)	(-2.44)	(-2.22)	(-2.43)
Intercept	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Pseudo R2	0.4408	0.4585	0.4721	0.4929	0.4933	0.4938
N	681.0000	681.0000	681.0000	4984.0000	4984.0000	4984.0000

Table 11: Facial Traits and Forecast Accuracy – The Impact of Earnings Volatility

This table reports the OLS regression estimates of analyst facial traits on analyst forecast accuracy with sample partitioned by above (the high group) or below (the low group) contemporaneous median of earning volatility (I_{EV}). Earning volatility is measured as the standard deviation of seasonal earning changes estimated over the four-year period ending on the fiscal end date. The dependent variable is proportional mean absolute forecast error (*PMAFE*) calculated as the difference between the absolute forecast error for analyst *i* on firm *j* at time *t* and mean absolute forecast error for firm *j* at time *t* scaled by the mean absolute forecast error for firm *j* at time *t*. The facial traits (*APP*, *YO_AT*, and *DOM*) are derived by calculating the ordinal ranking among all analysts following the same two-digits *SICs* at year *t*, adjusted by the total number of analysts following the same industry and year to standardize to [0,1]. Column (1) to (3) reports the estimation results for sample of forecasts of low group; Column (4) to (6) reports the estimation results for sample of forecasts of high group. All continuous variables are winsorized at 1% and 99 % level to avoid the extreme effects of outliers. All estimations have controlled year and 4 digits SIC industry fixed effects. All coefficients are multiplied by 100. ***, **, * denotes for significance at the 1%, 5% and 10% level, respectively.

	Low (Below Median)			**High (Above Median)**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
APP	-1.4201			-4.4947***		
	(-1.27)			(-4.89)		
YO_AT		-0.0583			0.6470	
		(-0.05)			(0.67)	
DOM			-2.1418*			-2.5089***
			(-1.74)			(-2.64)
NO_FOLLOWING	0.0550	0.0586	0.0646	-0.0501	-0.0534	-0.0532
	(0.38)	(0.41)	(0.45)	(-0.43)	(-0.46)	(-0.46)
DTOP10	2.6798*	2.6784*	2.6207*	-2.2489*	-2.1349*	-2.0780
	(1.78)	(1.78)	(1.74)	(-1.76)	(-1.67)	(-1.62)
DGEXP	0.1695*	0.1707*	0.1782**	0.0927	0.0955	0.0954
	(1.90)	(1.86)	(1.97)	(1.34)	(1.36)	(1.38)
DFEXP	-0.4850***	-0.4903***	-0.4986***	-0.0953	-0.1042	-0.1052
	(-3.06)	(-3.09)	(-3.15)	(-0.81)	(-0.88)	(-0.89)
DAGE	0.1346**	0.1350**	0.1464***	0.0143	0.0218	0.0319
	(2.39)	(2.40)	(2.63)	(0.36)	(0.55)	(0.80)
DHORIZON	0.2592***	0.2591***	0.2592***	0.3132***	0.3130***	0.3130***
	(27.22)	(27.21)	(27.23)	(34.40)	(34.38)	(34.38)
DSIC2	1.2495***	1.2425***	1.2270***	0.3347	0.3197	0.3015
	(3.86)	(3.82)	(3.75)	(1.36)	(1.29)	(1.22)
DPORTFOLIO_SIZE	-0.0437	-0.0427	-0.0428	-0.0784**	-0.0738**	-0.0782**
	(-1.03)	(-1.00)	(-1.01)	(-2.38)	(-2.25)	(-2.39)
SIZE	-0.4871**	-0.4835**	-0.4740**	0.1738	0.1759	0.1952
	(-2.06)	(-2.04)	(-2.00)	(0.84)	(0.85)	(0.94)
BM	0.0207	0.0250	0.0455	0.2618*	0.2526	0.2605*
	(0.09)	(0.10)	(0.19)	(1.69)	(1.62)	(1.66)
RET_{6M}	1.1217	1.1249	1.1146	0.6725	0.6667	0.6752
	(1.32)	(1.33)	(1.31)	(0.89)	(0.89)	(0.90)
Intercept	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Adjusted R2	0.0210	0.0210	0.0211	0.0306	0.0302	0.0303
N	93287	93287	93287	95391	95391	95391

Table 12: Facial Traits and the Propensity of Herding to Management Earnings Guidance

This table reports the Logit regression estimates of analyst facial traits on the difference between management guidance and analyst forecast. The difference between management guidance and analyst forecast is dummy indicator ($I_{|MF\text{-}AF|}$) taking 1 if the absolute value of the difference between analyst forecasts and management guidance is less than equal to 1 cent. The facial traits (*APP*, *YO_AT*, and *DOM*) are derived by calculating the ordinal ranking among all analysts following the same two-digits *SIC* at year *t*, adjusted by the total number of analysts following the same industry and year to standardize to [0,1]. All continuous variables are winsorized at 1% and 99 % level to avoid the extreme effects of outliers. All estimations have controlled year and 4 digits SIC industry fixed effects; standard errors are estimated by two-way clustering at firm and analyst level with t-statistics presented in parentheses. ***, **, * denotes for significance at the 1%, 5% and 10% level, respectively.

	(1)	(2)	(3)
APP	0.1260**		
	(1.99)		
YO_AT		0.0990	
		(1.55)	
DOM			-0.1433**
			(-2.10)
TOP10	0.0160	0.0081	0.0046
	(0.27)	(0.14)	(0.08)
GEXP	0.0000	0.0000	0.0000
	(0.94)	(1.25)	(1.31)
FEXP	-0.0000	-0.0000	-0.0000
	(-0.93)	(-1.03)	(-1.09)
AGE	0.0015	0.0011	0.0017
	(0.67)	(0.52)	(0.77)
PORTFOLIO_SIZE	-0.0005	-0.0006	-0.0007
	(-0.29)	(-0.33)	(-0.39)
SIZE	-0.0395***	-0.0405***	-0.0389***
	(-2.75)	(-2.82)	(-2.70)
BM	-0.2436***	-0.2456***	-0.2436***
	(-5.09)	(-5.15)	(-5.12)
RET_{6M}	0.0788*	0.0804*	0.0798*
	(1.86)	(1.90)	(1.89)
Intercept	YES	YES	YES
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
Pseudo R2	0.0610	0.0609	0.0610
N	47096	47096	47096

Appendix

Table A1: Variable Definition and Sampling Process
Panel A: Variable Definition

Variable	Definition
FE	Analyst forecast error, calculated as the difference between analyst forecast value and actual realized value adjusted by price.
PMAFE	The proportional mean absolute forecast error calculated as the difference between the absolute forecast error (*AFE*) for analyst *i* on firm *j* at time *t* and mean absolute forecast error (*MAFE*) for firm *j* at time *t* scaled by the mean absolute forecast error for firm *j* at time *t*.
APP	The ordinal ranking of an analyst's approachability score among all analysts following the same two-digits *SICs* at year *t,* adjusted by the number of analysts following the same industry in the same year.
YO_AT	The ordinal ranking of an analyst's youthfulness and attractiveness score among all analysts following the same two-digits *SICs* at year t, adjusted by the number of analysts in the same industry in the same year.
DOM	The ordinal ranking of an analyst's dominance score among all analysts following the same two-digits *SICs* at year *t,* adjusted by the number of analysts following the same industry in the same year.
APP_O	The orthogonal transformed ordinal ranking of an analyst's approachability score among all analysts following the same two-digits *SICs* at year *t,* adjusted by the number of analysts following the same industry in the same year.
YO_AT _O	The orthogonal transformed ordinal ranking of an analyst's youthfulness and attractiveness score among all analysts following the same two-digits *SICs* at year t, adjusted by the number of analysts in the same industry in the same year.
DOM_O	The orthogonal transformed ordinal ranking of an analyst's dominance score among all analysts following the same two-digits *SICs* at year *t,* adjusted by the number of analysts following the same industry in the same year.
fWHR	Analyst *i*'s facial width-to-height ratio, measured as the distance between the left and right zygion relative to the distance between the upper lip and the highest point of the eyelids.
I_{FEMALE}	Indicator variable is one if an analyst is female, and is zero if is male.
I_{JUNIOR}	Indicator variable is one if an analyst is in her first two years following an industry.
I_{EV}	Indicator variable is one if firm *i*'s earning volatility is above contemporaneous median. Earning volatility is measured as the standard deviation of seasonal earning changes estimated over the four-year period ending on the fiscal end date.
$I_{\|MF\text{-}AF\|}$	Indicator variable captures the difference between management guidance and analyst forecast. The dummy indicator is coded as 1 if the absolute value of the difference between analyst forecasts and management guidance is less than equal to 1 cent and 0 otherwise.
BOLD	Analyst boldness is measured by the percentage of bold forecasts of all forecasts for analyst *i* in industry *k* at year *t*. A forecast is coded as bold forecast if it is greater (less) than both her own previous forecast and the consensus forecast.
NO_FOLLOWING	Number of firms followed by analysts *i* in year *t.*
DSIC2	Number of two-digit *SICs* followed by analyst *i* at time *t* (*SIC2*) minus the average number of two-digit *SICs* followed by all I/B/E/S/analysts following firm *j* at time *t*.
DGEXP	The total number of years that analyst *i* appeared in I/B/E/S (*GEXP*) minus the average tenure of all I/B/E/S/ analysts supplying earnings forecasts for firm *j* at time *t*.
DFEXP	The total number of years since analyst's *i* first earnings forecast for firm *j* (*FEXP*) minus the average number of years of all I/B/E/S analysts supply earnings forecasts for firm *j* at time *t*.
DHORIZON	The age of analyst's *i* forecast (*HORIZON*) minus the average age of forecasts issued by all I/B/E/S/ analysts following firm *j* at time *t*, where horizon is defined as the age of forecasts in days at the minimum forecast horizon date.

DAGE	The age of analyst *i* in year *t* (*AGE*, inferred age of analyst *i* in year *t* using his/her LinkedIn profile) minus the mean of analysts' *AGE* following the same two-digits *SICs* in year *t*.
DPORTFOILIOSIZE	The number of firms followed by analyst *i* for firm *j* at time *t* (*Portfolio size*) minus the average number of firms followed by all I/B/E/S/ analysts supplying earnings forecasts for firm *j* at time *t*.
SIZE	The natural log of market capitalization (*ME*) of the covered firm (in $ millions) by the end of the month prior to the earnings forecast.
ME	The market capitalization of the covered firm (in $ millions) at the end of the month prior to the earnings forecast.
BM	Book value of equity in the fiscal year prior to the earnings forecast divided by the current market value of equity.
RET_{6M}	CRSP value-weighted index-adjusted buy-and hold abnormal return (*RET6Ms*) over the six months prior to the announcement date of the earnings forecast.
CALL	The natural logarithm of the one plus number of conference calls analyst *i* participated in year *t*.
PAGE	The mean of the natural logarithm of the number of pages of all analyst reports written by analyst *i* in year *t*.
STAR	Indicator variable is one if the analyst is named to Institutional Investor's all-star team in year *t*, and zero otherwise.
MEAN ERROR	The average *PMAFE* of all the firms covered by analyst *i* in year *t*.
TOTAL SIZE	The summation of market values of the all the firms covered by analyst *i* in year *t*.
BROKER SIZE	The number of unique I/B/E/S analysts of brokerage *i* in year *t*.

Panel B: Data Screening and Sampling Process

	EPS Revisions	**Firms**	**Analysts**
Obtain all analysts' quarter EPS forecasts over the 1990 to 2017 period from I/B/E/S, and Keep the last quarter earnings forecast with a horizon larger than 10 days and has a non-missing *PMAFE*	2,780,940	21,449	18,942
Search on Thomson Reuter Investtext for analyst full name and brokerage	--	--	4,701
Download LinkedIn profile by manually searching and matching their brokerage firm, last name and first name.	641,011	12,836	2,050
Merge with CRSP and COMPUSTAT to obtain stock price data and firm characteristics	426,486	7,737	1,566
Delete samples without profile pictures and/or samples with machine unidentifiable low-quality pictures.	190,600	5,905	795

Table A2: Difference Between Analysts Registered/Non-Registered on Linkedin, and With/Without Photos
This table provides the grouped T-test result for forecast level characteristics between analyst with and without profile images. ***, **, * denotes for significance at the 1%, 5% and 10% level, respectively.

	Full I/B/E/S	Without LinkedIn	With LinkedIn			Diff. (4) – (5)	Diff (4) – (1)
Variables	**(1)**	**(2)**	**(3) All**	**(4) With Photo**	**(5) Without Photo**		
PMAFE	-0.0055	-0.0019	-0.0185	-0.0174	-0.0194	0.0020	-0.0119***
TOP10	0.4315	0.0536	0.0591	0.0603	0.0579	0.0025***	-0.3712***
GEXP	7.5545	7.2342	8.6977	8.6801	8.7141	-0.0340	1.1256***
FEXP	3.0729	2.9722	3.4323	3.3917	3.4704	-0.0787***	0.3188***
HORIZON	79.4978	80.7419	75.058	74.7072	75.3875	-0.6803***	-4.7906***
SIC2	46.9083	46.9425	46.7863	46.9909	46.5942	0.3967***	0.0826*
PORTFOLIO_SIZE	25.2592	25.0706	25.9322	25.8614	25.9987	-0.1373***	0.6022***
Observation	**1798215**	**1404623**	**393592**	**190600**	**202992**		

Table A3: Facial Traits and Forecast Accuracy - Controlling for fWHR

This table reports summary statistics of analyst facial width-to-height ratio (*fWHR*) and regression estimates after controlling for facial width-to-height ratio (*fWHR*). Panel A reports the pair wise correlation between three facial traits and facial width-to-height ratio (fWHR). * indicates Pearson correlation coefficients significance at 5% level. Panel B reports the OLS regression estimates of analyst facial traits on analyst forecast accuracy including facial width-to-height ratio (fWHR) as control variable. The dependent variable is proportional mean absolute forecast error (*PMAFE*) calculated as the difference between the absolute forecast error for analyst *i* on firm *j* at time *t* and mean absolute forecast error for firm *j* at time *t* scaled by the mean absolute forecast error for firm *j* at time *t*. The facial traits (*APP*, *YO_AT*, and *DOM*) are derived by calculating the ordinal ranking among all analysts following the same two-digits *SICs* at year *t*, adjusted by the total number of analysts following the same industry and year to standardize to [0,1]. Column (1) to (3) reports estimation results by iteratively adding three facial traits into model. All continuous variables are winsorized at 1% and 99 % level to avoid the extreme effects of outliers. All estimations have controlled year and industry fixed effects; standard errors are estimated by two-way clustering at firm and analyst level with t-statistics presented in parentheses. All coefficients are multiplied by 100. ***, **, * denotes for significance at the 1%, 5% and 10% level, respectively.

Panel A: Correlation Between Facial Traits and fWHR

	APP	***YO_AT***	***DOM***	***fWHR***
APP	1.0000			
YO_AT	0.1308*	1.0000		
DOM	-0.0795*	-0.4251*	1.0000	
fWHR	-0.1008*	0.0669*	0.0709*	1.0000

Panel B: Regression Results

	(1)	**(2)**	**(3)**
APP	-3.2914***		
	(-3.97)		
YO_AT		0.3573	
		(0.40)	
DOM			-2.3023***
			(-2.67)
fWHR	-4.1869	-3.3159	-2.7845
	(-1.29)	(-1.00)	(-0.88)
NO_FOLLOWING	0.0240	0.0280	0.0310
	(0.24)	(0.28)	(0.31)
DTOP10	0.4049	0.4320	0.4456
	(0.38)	(0.41)	(0.42)
DGEXP	0.1214**	0.1246**	0.1285**
	(2.01)	(2.01)	(2.11)
DFEXP	-0.2750**	-0.2845***	-0.2890***
	(-2.55)	(-2.63)	(-2.68)
DAGE	0.0823**	0.0848**	0.0948***
	(2.28)	(2.36)	(2.65)
DHORIZON	0.3021***	0.3021***	0.3021***
	(42.36)	(42.33)	(42.37)
DSIC2	0.8899***	0.8728***	0.8547***
	(4.03)	(3.94)	(3.83)
DPORTFOLIO_SIZE	-0.0741***	-0.0708***	-0.0732***
	(-2.71)	(-2.59)	(-2.67)
SIZE	-0.0636	-0.0597	-0.0457
	(-0.39)	(-0.37)	(-0.28)

BM	0.1089	0.1086	0.1208
	(0.80)	(0.79)	(0.87)
RET_{6M}	0.9100	0.9123	0.9099
	(1.57)	(1.57)	(1.57)
Intercept	YES	YES	YES
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
Adjusted R2	0.0229	0.0228	0.0229
N	190600	190600	190600

Table A4: Facial Traits, Forecast Accuracy - Ethnicity

This table reports summary of analyst ethnicity and regression estimates after controlling for ethnicity fixed effect. Panel A summarize analyst ethnicity by tabulate ethnicity frequency at both forecast and analyst level. Analyst ethnicity is inferred from last name by using Python module Ethnicolr available at https://ethnicolr.readthedocs.io. The module utilizes US census data to predict and ethnicity based on last name. Each analyst is categorized into nh_white (non-Hispanic white), asian (Asian), nb_black (non-Hispanic black) or hispanic (Hispanic). Panel B reports the OLS regression estimates of analyst facial traits on analyst forecast accuracy and the dependent variable is proportional mean absolute forecast error (*PMAFE*) calculated as the difference between the absolute forecast error for analyst *i* on firm *j* at time *t* and mean absolute forecast error for firm *j* at time *t* scaled by the mean absolute forecast error for firm *j* at time *t*. Panel C reports the OLS regression estimates of analyst facial traits on star analyst and the dependent variable is a dummy variable taking 1 if analyst *i* is voted as star analyst in *t+1* and takes 0 otherwise. The facial traits (*APP*, *YO_AT*, and *DOM*) are derived by calculating the ordinal ranking among all analysts following the same two-digits *SICs* at year *t*, adjusted by the total number of analysts following the same industry and year. Column (1) to (3) reports the estimation results by including each of three facial traits. All continuous variables are winsorized at 1% and 99 % level to avoid the extreme effects of outliers. All estimations have controlled year, industry and analyst ethnicity fixed effects; standard errors are estimated by two-way clustering at firm and analyst level with t-statistics presented in parentheses. All coefficients are multiplied by 100. ***, **, * denotes for significance at the 1%, 5% and 10% level, respectively.

Panel A: Summary Statistics

Ethnicity	**Freq.**	**Percent**	**Cum.**
nh_white	172,291	90.39	90.39
asian	13,839	7.26	97.65
nb_black	2,673	1.40	99.06
hispanic	1,797	0.94	100.00
Total	190,600	100.00	

Panel B: Facial Traits and Forecast Accuracy - Ethnicity Fixed Effect

	(1)	**(2)**	**(3)**
APP	-3.2898***		
	(-4.29)		
YO_AT		0.2163	
		(0.27)	
DOM			-2.4527***
			(-2.99)
NO_FOLLOWING	-0.0148	-0.0112	-0.0081
	(-0.16)	(-0.12)	(-0.08)
DTOP10	0.5109	0.5363	0.5404
	(0.51)	(0.54)	(0.54)
DGEXP	0.1377**	0.1410**	0.1465**
	(2.41)	(2.40)	(2.54)
DFEXP	-0.2619***	-0.2712***	-0.2760***
	(-2.59)	(-2.67)	(-2.73)
DAGE	0.0526	0.0556	0.0604
	(1.11)	(1.17)	(1.28)
DSIC2	0.8171***	0.8020***	0.7852***
	(3.95)	(3.86)	(3.76)
DHORIZON	0.2853***	0.2852***	0.2853***
	(43.06)	(43.03)	(43.06)
DPORTFOLIO_SIZE	-0.0646**	-0.0619**	-0.0650**
	(-2.46)	(-2.36)	(-2.48)
SIZE	-0.1383	-0.1329	-0.1212
	(-0.88)	(-0.84)	(-0.77)

BM	0.1197	0.1188	0.1303
	(0.89)	(0.88)	(0.95)
RET_{6M}	1.1042**	1.1020**	1.0989*
	(1.97)	(1.96)	(1.96)
Intercept	YES	YES	YES
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
Ethnicity FE	YES	YES	YES
Adjusted R2	0.0235	0.0233	0.0234
N	190600	190600	190600

Panel C: Facial Traits and All-Star Analyst Election Outcome - Ethnicity Fixed Effect

	(1)	(2)	(3)
APP	0.4933**		
	(2.21)		
YO_AT		0.7043***	
		(3.00)	
DOM			-0.2072
			(-0.90)
LAG_STAR	3.6810***	3.6910***	3.6790***
	(21.06)	(21.27)	(21.06)
SIC2	0.0053	0.0064	0.0057
	(1.32)	(1.62)	(1.43)
PORTFOLIO_SIZE	0.0194***	0.0207***	0.0201***
	(3.19)	(3.45)	(3.33)
BROKER_SIZE	0.0425***	0.0427***	0.0429***
	(6.34)	(6.45)	(6.48)
MEAN_ERROR	-0.0605	-0.0439	-0.0547
	(-0.39)	(-0.29)	(-0.36)
TOTAL_SIZE	0.0065	0.0065	0.0063
	(1.57)	(1.57)	(1.54)
AGE	-0.0129	-0.0101	-0.0122
	(-1.63)	(-1.26)	(-1.53)
Intercept	YES	YES	YES
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
Ethnicity FE	YES	YES	YES
Pseudo R2	0.4741	0.4755	0.4727
N	5615	5615	5615

Table A5: Orthogonal Transformed Facial Traits Ranking

This table reports summary of analyst ethnicity and regression estimates using orthogonal transformed facial traits rankings. Panel A reports the OLS regression estimates of orthogonal transformed analyst facial traits on analyst forecast accuracy and all-star election results. The dependent variable is proportional mean absolute forecast error (*PMAFE*) calculated as the difference between the absolute forecast error for analyst *i* on firm *j* at time *t* and mean absolute forecast error for firm *j* at time *t* scaled by the mean absolute forecast error for firm *j* at time *t*. Panel B reports the OLS regression estimates of orthogonal transformed analyst facial traits on star analyst. The dependent variable is a dummy variable taking 1 if analyst *i* is voted as star analyst in *t+1* and takes 0 otherwise. The facial traits (*APP_O*, *YO_AT_O*, and *DOM_O*) are derived by calculating the orthogonal transformed ordinal ranking among all analysts following the same two-digits *SICs* at year *t*, adjusted by the total number of analysts following the same industry and year, orthogonalization is achieved via the modified Gram–Schmidt process (Golub and VanLoan, 1996). All continuous variables are winsorized at 1% and 99 % level to avoid the extreme effects of outliers. All estimations have controlled year and industry fixed effects; standard errors are estimated by two-way clustering at firm and analyst level with t-statistics presented in parentheses. All coefficients are multiplied by 100. ***, **, * denotes for significance at the 1%, 5% and 10% level, respectively.

Panel A: Orthogonal Transformed Facial Traits Ranking and Forecast Accuracy

	(1)
APP_O	-0.8820***
	(-4.00)
YO_AT_O	0.0363
	(0.16)
DOM_O	-0.7870***
	(-3.43)
NO_FOLLOWING	-0.0025
	(-0.03)
DTOP10	0.3726
	(0.37)
DGEXP	0.1184**
	(2.04)
DFEXP	-0.2627***
	(-2.60)
DAGE	0.0870**
	(2.54)
DHORIZON	0.2859***
	(43.13)
DSIC2	0.7834***
	(3.74)
DPORTFOLIO_SIZE	-0.0679***
	(-2.60)
SIZE	-0.1054
	(-0.67)
BM	0.1469
	(1.09)
RET_{6M}	1.1110**
	(1.98)
Intercept	YES
Industry FE	YES
Year FE	YES

Adjusted R2	0.0227
N	190600

Panel B: Orthogonal Transformed Facial Traits Ranking and All-Star Analyst Election

	(1)
APP_O	0.1473**
	(2.22)
YO_AT_O	0.1957***
	(2.86)
DOM_O	0.0839
	(1.20)
LAG_STAR	3.7394***
	(21.55)
SIC2	0.0065
	(1.60)
PORTFOLIO_SIZE	0.0189***
	(3.16)
BROKER_SIZE	0.0429***
	(6.47)
MEAN_ERROR	-0.0450
	(-0.33)
TOTAL_SIZE	0.0050
	(1.22)
AGE	-0.0057
	(-0.75)
Intercept	YES
Industry FE	YES
Year FE	YES
Pseudo R2	0.4734
N	5713

Table A6: The Impact of Reg-FD – Additional Analysis

This table reports additional analysis of the impact of Reg-FD using a shorter window and cohort sample. Panel A reports the OLS regression estimates of analyst facial traits on analyst forecast accuracy by splitting the overall sample into pre and post Reg-TD periods. Sample period is restricted to within [-5, 5] years range of Reg-FD. Panel B reports the OLS regression estimates of analyst facial traits on analyst forecast accuracy by splitting the overall sample into pre and post Reg-TD periods. Sample period is restricted to a constant sample requiring analyst appearing in both pre and post periods within [-5, 5] years range of Reg-FD. The dependent variable is proportional mean absolute forecast error (*PMAFE*) calculated as the difference between the absolute forecast error for analyst *i* on firm *j* at time *t* and mean absolute forecast error for firm *j* at time *t* scaled by the mean absolute forecast error for firm *j* at time *t*. The facial traits (*APP*, *YO_AT*, and *DOM*) are derived by calculating the ordinal ranking among all analysts following the same two-digits *SICs* at year *t*, adjusted by the total number of analysts following the same industry and year to standardize to [0,1]. Column (1) to (3) reports the estimation results for overall sample; Column (4) to (6) reports the estimation results for pre-Reg-FD sample and Column (7) to (9) reports the estimation results for post Reg-FD period. All continuous variables are winsorized at 1% and 99 % level to avoid the extreme effects of outliers. All estimations have controlled year and 4 digits SIC industry fixed effects; standard errors are estimated by two-way clustering at firm and analyst level with t-statistics presented in parentheses. All coefficients are multiplied by 100. ***, **, * denotes for significance at the 1%, 5% and 10% level, respectively.

Panel A: Shorter Window Analysis

	Overall Sample (1995 - 2005)			Pre Reg-FD (1995 - 2000)			Post Reg-FD (2000 - 2005)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
APP	-3.0066**			-2.4637			-3.2284**		
	(-2.27)			(-0.96)			(-2.00)		
YO_AT		-0.0486			-4.2327*			0.4488	
		(-0.04)			(-1.67)			(0.28)	
DOM			-3.4629**			-0.6622			-3.7430**
			(-2.57)			(-0.26)			(-2.29)
NO_FOLLOWING	-0.2953	-0.3007	-0.2975	-0.8211	-0.8286	-0.8159	-0.0740	-0.0758	-0.0725
	(-1.31)	(-1.33)	(-1.32)	(-1.41)	(-1.42)	(-1.40)	(-0.29)	(-0.30)	(-0.28)
DTOP10	3.5532*	3.8728*	3.7557*	3.0979	3.7813	3.3896	3.9379*	4.2655*	4.0810*
	(1.75)	(1.91)	(1.86)	(0.70)	(0.86)	(0.77)	(1.74)	(1.89)	(1.81)
DGEXP	-0.0989	-0.0822	-0.0460	-1.0114**	-1.0515**	-0.9749**	0.0067	0.0275	0.0544
	(-0.61)	(-0.50)	(-0.28)	(-2.21)	(-2.27)	(-2.11)	(0.04)	(0.16)	(0.31)
DFEXP	0.1501	0.1593	0.1506	0.6115	0.6474	0.6109	0.1448	0.1514	0.1544
	(0.65)	(0.69)	(0.65)	(1.09)	(1.15)	(1.08)	(0.57)	(0.59)	(0.61)
DAGE	0.1457**	0.1386**	0.1342*	-0.0334	-0.0498	-0.0529	0.1994**	0.1973**	0.1955**
	(2.08)	(1.98)	(1.92)	(-0.23)	(-0.35)	(-0.38)	(2.49)	(2.46)	(2.44)
DHORIZON	0.3721***	0.3723***	0.3727***	0.4065***	0.4061***	0.4069***	0.3563***	0.3566***	0.3570***
	(26.67)	(26.67)	(26.70)	(14.47)	(14.46)	(14.44)	(21.96)	(21.99)	(22.01)
DSIC2	0.9806**	0.9921**	1.0008**	1.8893**	2.0124***	1.9209***	0.4266	0.4264	0.4501
	(2.20)	(2.22)	(2.24)	(2.55)	(2.72)	(2.59)	(0.76)	(0.76)	(0.80)
DPORTFOLIO_SIZE	-0.2032***	-0.2134***	-0.2214***	-0.0957	-0.1044	-0.1134	-0.2540***	-0.2622***	-0.2625***
	(-3.15)	(-3.31)	(-3.43)	(-0.84)	(-0.92)	(-0.98)	(-3.17)	(-3.27)	(-3.28)
SIZE	-0.3994	-0.4115	-0.3926	-0.3761	-0.3330	-0.3525	-0.5371	-0.5751*	-0.5534

	(-1.41)	(-1.46)	(-1.39)	(-0.76)	(-0.67)	(-0.71)	(-1.55)	(-1.66)	(-1.60)
BM	0.0658	0.0599	0.0602	-0.2647	-0.1969	-0.2615	0.1606	0.1476	0.1531
	(0.33)	(0.31)	(0.30)	(-0.43)	(-0.32)	(-0.42)	(0.84)	(0.78)	(0.80)
RET_{6M}	1.6159	1.6336	1.6199	1.8188	1.8009	1.8329	1.3079	1.3118	1.3045
	(1.59)	(1.60)	(1.59)	(1.17)	(1.16)	(1.18)	(0.95)	(0.96)	(0.95)
Intercept	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adjusted R2	0.0401	0.0400	0.0402	0.0591	0.0592	0.0590	0.0431	0.0429	0.0432
N	41747	41747	41747	13027	13027	13027	28720	28720	28720

Panel B: Shorter Window Cohort Sample Analysis

	Overall Sample (1995 - 2005)			**Pre Reg-FD (1995 - 2000)**			**Post Reg-FD (2000 - 2005)**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
APP	-4.7005***			-3.0574			-5.2756**		
	(-2.87)			(-1.05)			(-2.51)		
YO_AT		-1.9700			-5.7196*			-2.0483	
		(-1.21)			(-1.96)			(-0.98)	
DOM			-1.9711			-0.5062			-1.4533
			(-1.19)			(-0.17)			(-0.69)
NO_FOLLOWING	-0.4014	-0.4209	-0.4213	-0.7491	-0.7687	-0.7412	-0.1402	-0.1592	-0.1654
	(-1.46)	(-1.52)	(-1.53)	(-1.14)	(-1.17)	(-1.13)	(-0.44)	(-0.50)	(-0.52)
DTOP10	3.5988	4.0440	3.9942	1.4530	2.2891	1.9229	4.1771	4.4878	4.4814
	(1.36)	(1.54)	(1.52)	(0.28)	(0.45)	(0.37)	(1.38)	(1.48)	(1.48)
DGEXP	-0.0698	-0.0550	-0.0043	-1.1330**	-1.1858**	-1.1000**	0.0825	0.0937	0.1423
	(-0.34)	(-0.26)	(-0.02)	(-2.13)	(-2.22)	(-2.05)	(0.36)	(0.40)	(0.61)
DFEXP	0.2158	0.2448	0.2236	0.7118	0.7495	0.7189	0.1585	0.1945	0.1780
	(0.79)	(0.90)	(0.82)	(1.10)	(1.16)	(1.11)	(0.53)	(0.65)	(0.59)
DAGE	0.1500	0.1333	0.1263	0.0311	0.0141	0.0058	0.2161*	0.2084*	0.2018*
	(1.61)	(1.44)	(1.36)	(0.19)	(0.09)	(0.04)	(1.89)	(1.82)	(1.77)
DHORIZON	0.4381***	0.4383***	0.4389***	0.4807***	0.4806***	0.4815***	0.4138***	0.4140***	0.4145***
	(23.89)	(23.91)	(23.92)	(14.61)	(14.63)	(14.61)	(18.54)	(18.56)	(18.58)
DSIC2	1.3896**	1.4259***	1.4259***	2.4149***	2.5708***	2.4620***	0.7714	0.7395	0.7824

	(2.56)	(2.62)	(2.63)	(2.82)	(3.02)	(2.89)	(1.07)	(1.02)	(1.08)
DPORTFOLIO_SIZE	-0.2407***	-0.2581***	-0.2658***	-0.1496	-0.1531	-0.1688	-0.3108***	-0.3274***	-0.3294***
	(-3.09)	(-3.31)	(-3.40)	(-1.13)	(-1.17)	(-1.26)	(-3.09)	(-3.25)	(-3.27)
SIZE	-0.1025	-0.1332	-0.1251	-0.2337	-0.1864	-0.2166	-0.2252	-0.3081	-0.3011
	(-0.31)	(-0.41)	(-0.38)	(-0.43)	(-0.34)	(-0.39)	(-0.53)	(-0.73)	(-0.71)
BM	0.1083	0.0956	0.0868	-0.4306	-0.3480	-0.4280	0.3169	0.2926	0.2861
	(0.49)	(0.44)	(0.40)	(-0.65)	(-0.53)	(-0.64)	(1.42)	(1.34)	(1.29)
RET_{6M}	2.0204*	2.0534*	2.0451*	1.9838	1.9765	1.9959	2.4194	2.4278	2.4413
	(1.68)	(1.70)	(1.69)	(1.13)	(1.13)	(1.14)	(1.43)	(1.43)	(1.44)
Intercept	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adjusted R2	0.0451	0.0449	0.0449	0.0640	0.0643	0.0639	0.0479	0.0476	0.0475
N	34032	34032	34032	12217	12217	12217	21815	21815	21815

Table A7: Facial Traits and Forecast Accuracy in Non-Photoshopped Sample

This table provides summary statistics and estimation results of analyst facial traits to forecast accuracy in a non-photoshopped sample. Panel A provides the detailed summary statistics of photoshopped probability of each analyst image forecast level and analyst level. Each image is analyzed by a deep machine learning model proposed and open-sourced by Peter Wang and his team. Codes, models and related paper is available at Github repo at https://github.com/PeterWang512/FALdetector. The output of the machine learning model is a float number between 0 and 1 indicating the probability the input image is being photoshopped. Panel B reports the OLS regression estimates of analyst facial traits on analyst forecast accuracy in a non-photoshopped sample. Specifically, images with photoshopped probability greater than or equal to 10% are dropped from this estimation sample. In all, 2516 observations issued by 12 analysts are eliminated. The dependent variable is proportional mean absolute forecast error (*PMAFE*) calculated as the difference between the absolute forecast error for analyst *i* on firm *j* at time *t* and mean absolute forecast error for firm *j* at time *t* scaled by the mean absolute forecast error for firm *j* at time *t*. The facial traits (*APP*, *YO_AT*, and *DOM*) are derived by calculating the ordinal ranking among all analysts following the same two-digits *SICs* at year *t*, adjusted by the total number of analysts following the same industry and year to standardize to [0,1]. Column (1) to (3) reports the estimation results by including each of three facial traits. All continuous variables are winsorized at 1% and 99 % level to avoid the extreme effects of outliers. All estimations have controlled year and industry fixed effects; standard errors are estimated by two-way clustering at firm and analyst level with t-statistics presented in parentheses. All coefficients are multiplied by 100. ***, **, * denotes for significance at the 1%, 5% and 10% level, respectively.

Panel A: Summary of the Probability of Photoshopped Images

Variable	N	Mean	SD	P1	P25	Median	P75	P99
PROB	795	0.0075	0.0301	0.0000	0.0000	0.0001	0.0025	0.1553

Panel B: Estimation Result of Facial Traits and Forecast Accuracy in Non-Photoshopped Sample

	(1)	(2)	(3)
APP	-2.7492***		
	(-3.57)		
YO_AT		0.1068	
		(0.13)	
DOM			-2.1293***
			(-2.61)
NO_FOLLOWING	-0.0005	0.0024	0.0051
	(-0.01)	(0.03)	(0.05)
DTOP10	0.4563	0.4817	0.4831
	(0.45)	(0.48)	(0.48)
DGEXP	0.1277**	0.1297**	0.1347**
	(2.23)	(2.21)	(2.33)
DFEXP	-0.2267**	-0.2340**	-0.2384**
	(-2.24)	(-2.30)	(-2.35)
DAGE	0.0760**	0.0796**	0.0889**
	(2.17)	(2.28)	(2.57)
DHORIZON	0.2839***	0.2838***	0.2839***
	(42.86)	(42.81)	(42.85)
DSIC2	0.8297***	0.8183***	0.8035***
	(3.95)	(3.88)	(3.79)
DPORTFOLIO_SIZE	-0.0674**	-0.0643**	-0.0670**
	(-2.56)	(-2.45)	(-2.55)
SIZE	-0.1305	-0.1245	-0.1141
	(-0.83)	(-0.79)	(-0.72)
BM	0.1227	0.1223	0.1335
	(0.92)	(0.91)	(0.99)
RET_{6M}	1.0668*	1.0667*	1.0663*

	(1.90)	(1.89)	(1.89)
Intercept	YES	YES	YES
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
Adjusted R2	0.0224	0.0223	0.0224
N	188084	188084	188084

Figures and Illustrations

Figure 1: Screenshot of LinkedIn Profile
This screenshot is sample sell-side analyst profile that we collected from LinkedIn.com. The profiles typically include comprehensive information such as name, position title, current location, working experience, education background as well as a high-resolution profile image.

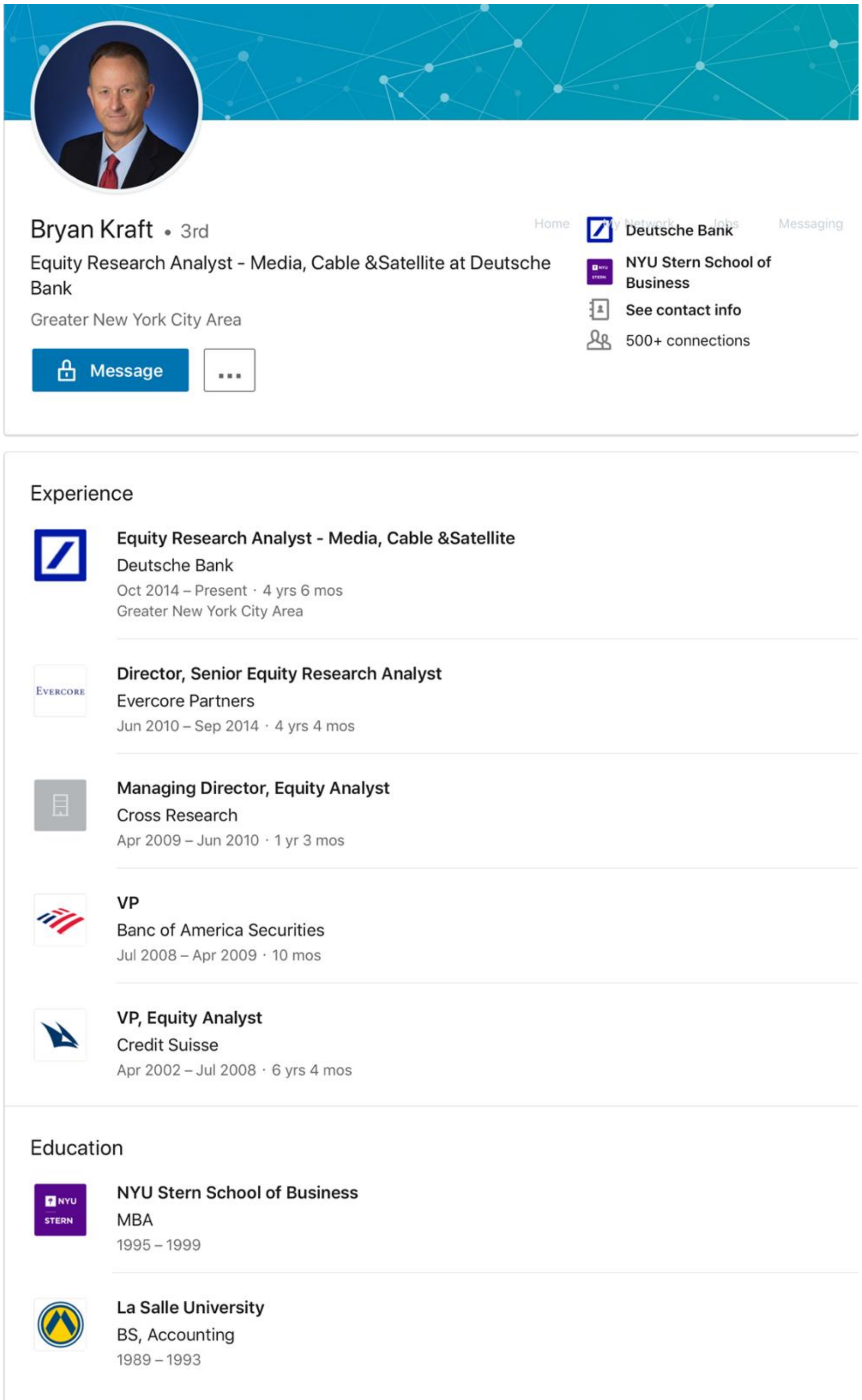
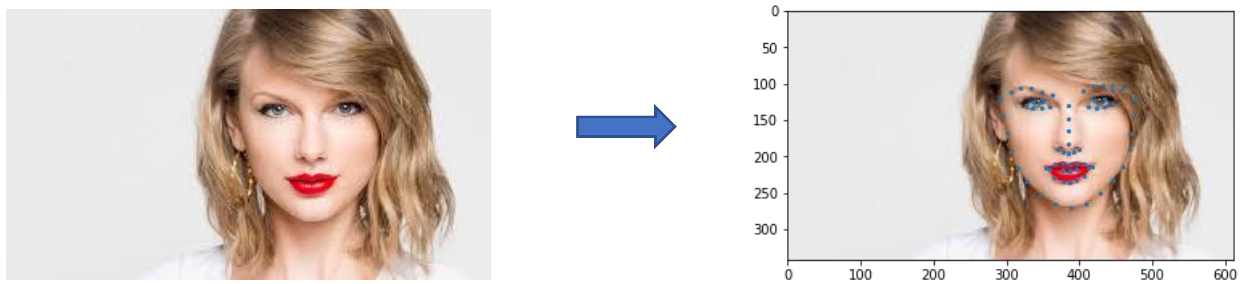


Figure 2 Illustration of Delineating Process

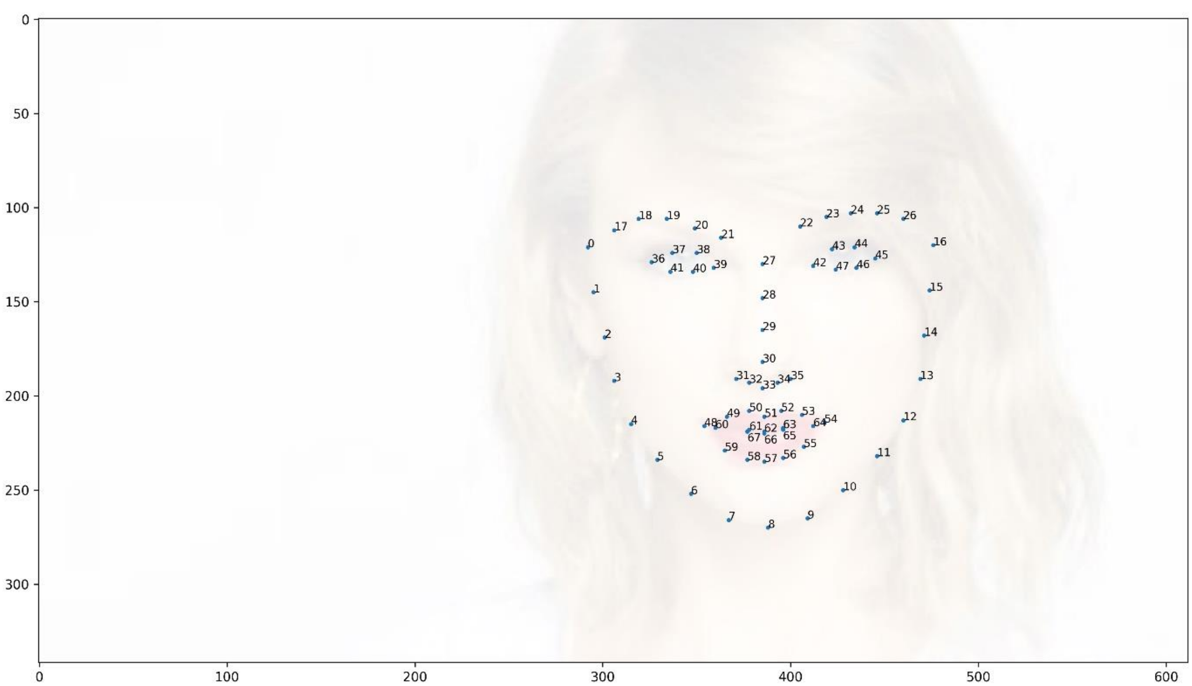
Panel A:

Pre-processing Pictures: rotate to orient faces, resize to similar head size, adjust brightness and contrast, remove non-clear pictures On each face, using FPA (a machine learning-neural network algorithm provided by C. Sagonas at Imperial College) to lay 68 fiducial landmark points. The delineating process is illustrated as follow. The image of Taylor Swift is copy-right free, downloaded from Getty Image



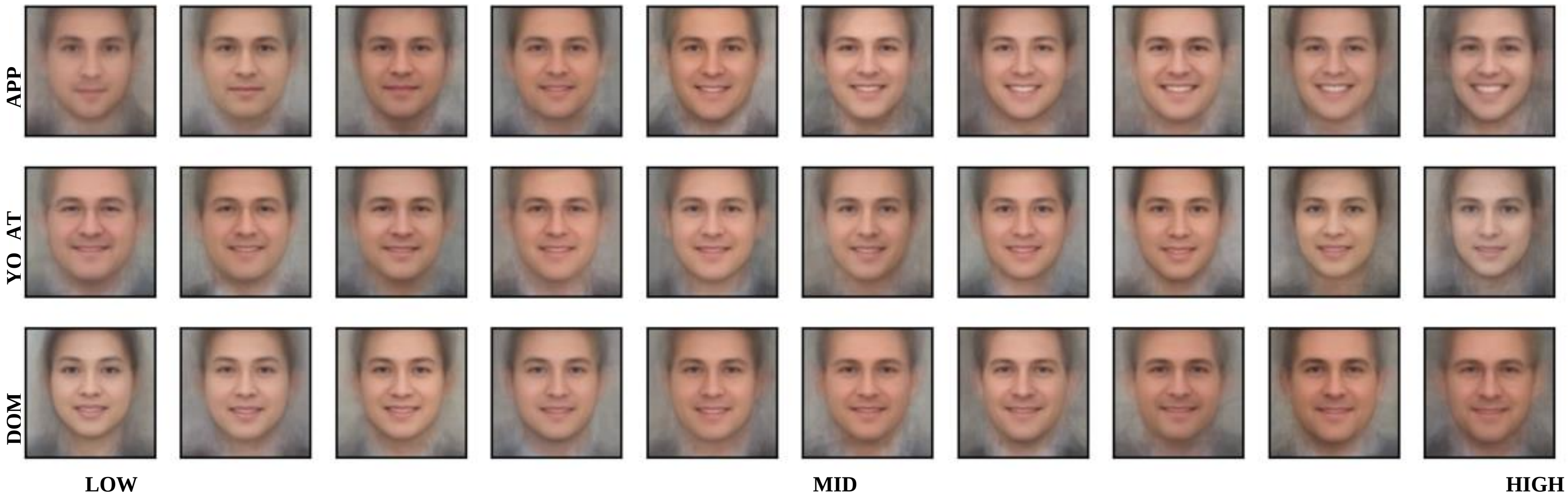
Panel B: Illustration of Facial Attributes Extraction Process

Following Vernon et al. (2014) we calculated 65 measures of the physical attributes of a face, including measures related to the size and shape of the face as a whole (e.g., head width), individual facial features (e.g., bottom lip curvature), their spatial arrangement (e.g., mouth-to-chin distance), the presence/absence of glasses and facial hair, and information about the texture and color of specified regions (e.g., average hue of pixels within polygons defined by fiducial points around the irises). Where applicable, size and area values were first standardized by dividing by a proxy for apparent head size. Figure 3 provides an example of the attribute extraction process. A list of attributes used in this study and their corresponding calculations are available in the appendix 5. The facial attributes extraction process is illustrated as follow. The image of Taylor Swift is copy-right free, downloaded from Getty Image



Panel C: Average Face

This figure illustrates the average face of each facial traits of each decile. The left-hand side average faces have lowest facial traits scores; while the right-hand side have the highest facial traits scores.



Online Appendix

Table OA1: List of 65 Facial Attributes and Calculation Description
The following table illustrate the calculation description for each of 65 facial traits. We adopt and modify Vernon's method by using 68 key fiducial landmarks instead of 179 to calculate 65 facial attributes.

No.	Attributes	Calculation Description
01.	Head area	Area enclosed by points 0:26
02.	Head height	Vertical distance between centroid of 7:9 and centroid of 19:24
03.	Head width	Horizontal distance between centroid of 15:16 and centroid of 0:1
04.	Head orientation 1	Absolute x axis coordinate of middle of nose (centroid of 27:36)
05.	Head orientation 2	Absolute y axis coordinate of middle of nose (centroid of 27:36)
06.	Head title	Return 0 since images are standardized profile images
07.	Eyebrow area	Area enclosed by points 17:21, 22:26
08.	Eyebrow height	Vertical distance between centroid of 17, 21, 22, 26 and centroid of 18:20, 23:25
09.	Eyebrow width	Horizontal distance between points 21,26 and points 17, 22
10.	Eyebrow gradient	Absolute gradient of linear polynomial fitted through points 19:21
11.	Eye area	Average of areas enclosed by points 36:41 and 42:47
12.	Iris area	Average of area enclosed by points 37:41 and 43:47
13.	Eye height	Vertical distance between centroid of 40,41,46,47 and centroid of 37,38,43,44
14.	Eye width	Horizontal distance between points 39,45 and 36,42
15.	% Iris	$(1/\pi r^2)$*Iris area, where r is 1/2 of eye height
16.	Nose area	Average of area enclosed by points 30:35, 27,30,31 and 27,30,35
17.	Nose height	Vertical distance between points 33 and 27
18.	Nose width	Horizontal distance between points 35 and 31
19.	Nose curve	Coefficient of x^2 from quadratic polynomial fitted through points 31:35
20.	Nose flare	Vertical distance between centroid of 34,32 and centroid of 31,35
21.	Jaw height	Vertical distance between centroid of 7,9 and centroid of 2,14
22.	Jaw gradient	Absolute gradient of linear polynomial fitted through points 6:8
23.	Jaw deviation	SD of distances between all points on jaw (2:14) and point at the top of the jaw (x = average of 2:14; y = average of 2,14)
24.	Chin curve	Coefficient of x^2 from quadratic polynomial fitted through points 6:10
25.	Mouth area	Area enclosed by points 48:59
26.	Mouth height	Vertical distance between centroid of 48:54 and centroid of 55:59, 48, 54
27.	Top lip height	Vertical distance between centroid of 48:54 and centroid of 60:64, 48, 54
28.	Bottom lip height	Vertical distance between centroid of 65:67, 48, 54 and centroid of 55:59, 48, 54
29.	Mouth width	Horizontal distance between points 54 and 48
30.	Mouth gap	Vertical distance between centroid of 65:67, 48, 54 and centroid of 60:63,48,54
31.	Top lip curve	Coefficient of x^2 from quadratic polynomial fitted through points 60:63, 48, 54
32.	Bottom lip curve	Coefficient of x^2 from quadratic polynomial fitted through points 65:67, 48, 54
33.	Nose line separation	Horizontal distance between centroid of 32,50 and centroid of 34,52
34.	Cheekbone position	Vertical distance between points 7,9 and points 2,3,31,48
35.	Cheek gradient	Absolute gradient of linear polynomial fitted through centroid of 2,3 and centroid of 31 48
36.	Eye line gradient	Absolute gradient of linear polynomial fitted through 27 and centroid of 39 and 28

37.	Eyes position	(1/head height) * (vertical distance between centroid of 7:9 and centroid of 36:47)
38.	Eyebrow position	(1/head height) * (vertical distance between centroid of 7:9 and centroid of 17:26)
39.	Mouth position	(1/head height) * (vertical distance between centroid of 7:9 and centroid of 48:59)
40.	Nose position	(1/head height) * (vertical distance between centroid of 7:9 and centroid of 27:35)
41.	Eye separation	Horizontal distance between centroid of 37:41and centroid of 43:47
42.	Eyes-to-mouth distance	Vertical distance between centroid of 39,42 and centroid of 50,52
43.	Eyes-to-eyebrows distance	Vertical distance between centroid of 17,21,22,26 and centroid of 27,28,43,44
44.	Left head to left eye	Horizontal distance between centroid of 0:2 and 36
45	Right head to right eye	Horizontal distance between centroid of 14:16 and 45
46.	Mouth-to-chin distance	Vertical distance between centroid of 56,58 and centroid of 7,9
47.	Mouth-to-nose distance	Vertical distance between centroid of 32:34 and centroid of 50:51
48.	Skin hue	
49.	Skin saturation	Color information (HSV format) for area enclosed by points points 0:16, 17:26
50.	Skin value	
51.	Eyebrow hue	
52.	Eyebrow saturation	Color information (HSV format) for area enclosed by points points 17:21,22:26
53.	Eyebrow value	
54.	Lip hue	
55.	Lip saturation	Color information (HSV format) for area enclosed by points points 48:59
56.	Lip value	
57.	Iris hue	
58.	Iris saturation	Color information (HSV format) for area enclosed by points points 37,38,40,41,43,44,46,47
59.	Iris value	
60.	Hue entropy	
61.	Saturation entropy	These attributed are based on Python module “scipy.stats.entropy”, used on the hue, saturation and value channels of the area classed as skin
62.	Value entropy	
63.	Glasses	Signifies whether the person has glasses (1) or not (0)
64.	Facial hair	Signifies whether the person has facial hair (beard, moustache; 1) or not (0)
65.	Stubble	Signifies whether the person has stubble (1) or not (0)

Table OA2: Facial Traits and Forecast Accuracy – Additional Robustness

This table reports additional robustness checks of the OLS regression estimates of analyst facial traits on analyst forecast accuracy. Panel A reports the OLS regression estimates of analyst facial traits on analyst forecast accuracy with gender adjusted facial traits rankings. The dependent variable is proportional mean absolute forecast error (*PMAFE*) calculated as the difference between the absolute forecast error for analyst *i* on firm *j* at time *t* and mean absolute forecast error for firm *j* at time *t* scaled by the mean absolute forecast error for firm *j* at time *t*. The facial traits (*APP*, *YO_AT*, and *DOM*) are derived by calculating the ordinal by gender ranking among all analysts following the same two-digits *SICs* at year *t*, adjusted by the total number of analysts of same gender in that industry year to standardize to [0,1]. Column (1) to (3) reports the estimation results by including each of three facial traits. All continuous variables are winsorized at 1% and 99 % level to avoid the extreme effects of outliers. All estimations have controlled year and industry fixed effects; standard errors are estimated by two-way clustering at firm and analyst level with t-statistics presented in parentheses. Panel B reports the OLS regression estimates of analyst facial traits on analyst forecast accuracy with additional age and brokerage fixed effects. The dependent variable is proportional mean absolute forecast error (*PMAFE*) calculated as the difference between the absolute forecast error for analyst *i* on firm *j* at time *t* and mean absolute forecast error for firm *j* at time *t* scaled by the mean absolute forecast error for firm *j* at time *t*. The facial traits (*APP*, *YO_AT*, and *DOM*) are derived by calculating the ordinal ranking among all analysts following the same two-digits *SICs* at year *t*, adjusted by the total number of analysts following the same industry and year. Column (1) to (3) reports the estimation results by including each of three facial traits with additional brokerage fixed effect; column (4) to (6) reports the estimation with additional age fixed effects and column (7) to (9) reports estimation results with additional both brokerage and age fixed effects. All continuous variables are winsorized at 1% and 99 % level to avoid the extreme effects of outliers. All estimations have controlled year, industry and brokerage fixed effects; standard errors are estimated by two-way clustering at firm and analyst level with t-statistics presented in parentheses. All coefficients are multiplied by 100. ***, **, * denotes for significance at the 1%, 5% and 10% level, respectively.

Panel A: Facial Traits and Forecast Accuracy – Gender Adjusted

	(1)	(2)	(3)
GAPP	-3.4191***		
	(-3.73)		
GYO_AT		-0.3536	
		(-0.37)	
GDOM			-3.3452***
			(-3.43)
NO_FOLLOWING	-0.0025	-0.0024	0.0037
	(-0.03)	(-0.02)	(0.04)
DTOP10	0.4270	0.3843	0.3162
	(0.43)	(0.39)	(0.32)
DGEXP	0.1187**	0.1187**	0.1263**
	(2.09)	(2.04)	(2.21)
DFEXP	-0.2614***	-0.2671***	-0.2725***
	(-2.58)	(-2.63)	(-2.69)
DAGE	0.0721**	0.0767**	0.0888***
	(2.09)	(2.24)	(2.60)
DHORIZON	0.2860***	0.2858***	0.2858***
	(43.17)	(43.11)	(43.15)
DSIC2	0.7871***	0.7902***	0.7741***
	(3.77)	(3.78)	(3.69)
DPORTFOLIO_SIZE	-0.0648**	-0.0617**	-0.0667**
	(-2.47)	(-2.35)	(-2.55)
SIZE	-0.1345	-0.1207	-0.1045
	(-0.86)	(-0.77)	(-0.67)
BM	0.1323	0.1309	0.1482
	(0.99)	(0.98)	(1.09)
RET_{6M}	1.1206**	1.1174**	1.1078**

	(2.00)	(1.99)	(1.97)
Intercept	YES	YES	YES
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
Adjusted R2	0.0226	0.0224	0.0225
N	190600	190600	190600

Panel B: Facial Traits and Forecast Accuracy –Additional Fixed Effects

	(1)	(2)	(3)						
APP	-2.8960***			-2.4435***			-3.1905***		
	(-3.70)			(-3.35)			(-4.06)		
YO_AT		0.6991			-0.1359			0.6674	
		(0.83)			(-0.17)			(0.78)	
DOM			-2.0706**			-1.5572**			-2.2178***
			(-2.47)			(-2.02)			(-2.61)
NO_FOLLOWING	0.0255	0.0280	0.0292	-0.0159	-0.0143	-0.0115	0.0222	0.0249	0.0263
	(0.27)	(0.29)	(0.31)	(-0.17)	(-0.15)	(-0.12)	(0.23)	(0.26)	(0.28)
DTOP10	1.3046	1.2762	1.3259	0.6646	0.7209	0.6907	1.4781	1.4400	1.4933
	(1.30)	(1.27)	(1.32)	(0.67)	(0.73)	(0.70)	(1.47)	(1.43)	(1.48)
DGEXP	0.1470**	0.1602***	0.1597***	0.1415**	0.1423**	0.1464**	0.7930***	0.7689***	0.7593***
	(2.48)	(2.63)	(2.66)	(2.44)	(2.40)	(2.51)	(3.69)	(3.57)	(3.51)
DFEXP	-0.2124**	-0.2199**	-0.2221**	-0.2578**	-0.2631***	-0.2673***	0.1753***	0.1889***	0.1895***
	(-2.11)	(-2.18)	(-2.20)	(-2.56)	(-2.60)	(-2.65)	(2.91)	(3.05)	(3.11)
DAGE	0.0241	0.0242	0.0338	0.0956***	0.0989***	0.1050***	-0.2229**	-0.2306**	-0.2328**
	(0.65)	(0.65)	(0.92)	(2.79)	(2.89)	(3.08)	(-2.21)	(-2.29)	(-2.31)
DHORIZON	0.2799***	0.2799***	0.2800***	0.2862***	0.2861***	0.2862***	0.0177	0.0199	0.0236
	(42.24)	(42.23)	(42.25)	(43.21)	(43.17)	(43.21)	(0.37)	(0.42)	(0.50)
DSIC2	0.7983***	0.7744***	0.7644***	0.8201***	0.8107***	0.7968***	0.2791***	0.2791***	0.2792***
	(3.67)	(3.55)	(3.49)	(3.94)	(3.88)	(3.80)	(42.12)	(42.11)	(42.13)
DPORTFOLIO_SIZE	-0.0631**	-0.0581**	-0.0597**	-0.0722***	-0.0696***	-0.0715***	-0.0623**	-0.0573**	-0.0591**
	(-2.28)	(-2.10)	(-2.16)	(-2.76)	(-2.67)	(-2.74)	(-2.25)	(-2.07)	(-2.14)
SIZE	-0.2943*	-0.2958*	-0.2829*	-0.1349	-0.1279	-0.1228	-0.2959*	-0.2967*	-0.2853*
	(-1.79)	(-1.79)	(-1.72)	(-0.86)	(-0.81)	(-0.78)	(-1.79)	(-1.79)	(-1.73)
BM	0.0001	-0.0031	0.0061	0.1056	0.1055	0.1137	-0.0079	-0.0110	-0.0024
	(0.00)	(-0.02)	(0.04)	(0.74)	(0.74)	(0.79)	(-0.05)	(-0.07)	(-0.02)
RET_{6M}	1.0610*	1.0751*	1.0703*	1.1423**	1.1445**	1.1429**	1.0309*	1.0431*	1.0375*
	(1.88)	(1.91)	(1.90)	(2.03)	(2.04)	(2.03)	(1.83)	(1.85)	(1.84)
Intercept	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Brokerage FE	YES	YES	YES				YES	YES	YES
Age FE				YES	YES	YES	YES	YES	YES
Adjusted R2	0.0303	0.0302	0.0302	0.0230	0.0229	0.0229	0.0311	0.0310	0.0311
N	190600	190600	190600	190600	190600	190600	190600.0000	190600.0000	190600.0000