Face Value: Trait Inference, Performance Characteristics, and Market Outcomes for Financial Analysts*

Lin Peng†, Siew Hong Teoh‡, Yakun Wang§, and Jiawen Yan*

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Abstract

Using machine learning-based algorithms, we extract key impressions about personality traits from the LinkedIn profile photos of sell-side analysts. We find that these face-based factors are associated with analyst behavior, performance, and capital- and labor-market outcomes. The trustworthiness (*TRUST*) and dominance (*DOM*) factors are positively associated with analyst forecast accuracy and report length. Analysts with high *TRUST* scores tend to herd with managerial guidance forecasts; those with high *DOM* scores actively participate in conference calls. The positive association of the attractiveness (*ATTRACT*) factor on forecast accuracy diminishes with market learning and after Reg-FD. Forecasts from analysts with higher *TRUST* and *DOM* scores generate stronger price reactions. High *DOM* scores help male analysts but hurt female analysts to attain All-Star status. These findings suggest that impressions formed from observing analysts' physical facial attributes are associated with analysts' economic behaviors. Some of the investor and peer responses to these impressions seem to reflect societal biases and gender stereotypes.

Keywords: Machine learning; Facial recognition; Personality traits; Analysts; Gender stereotypes; EPS forecasts; Conference calls; Herding; All-Star analysts

JEL classifications: G14; G24; G28; G41; D83; J16

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† Bert W. Wasserman Department of Economics and Finance, Zicklin School of Business, Baruch College, CUNY, One Bernard Baruch Way, New York, NY 10010. E-mail: lin.peng@baruch.cuny.edu.

‡ Paul Merage School of Business, University of California – Irvine, 4291 Pereira Drive SB1-3222, Irvine, CA 92697-3125. Email: steoh@uci.edu.

§ School of Management and Economics, The Chinese University of Hong Kong – Shenzhen, Email: wangyakun@cuhk.edu.cn.

* Cornell University, Email: jy937@cornell.edu.

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Abstract

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1. Introduction

Human faces convey a wealth of information about behavioral propensities and social interactions. Philosophers in classical antiquity have described the reading of character traits from facial appearances as early as the time of Aristotle. Since then, face reading has gone through cycles of acceptance and rejection by scientists. Recent advances in neuroscience and cognitive psychology suggest that faces are central to social cognition and that there are systematic, predictable relations between appearance and trait inferences (Hugenberg and Wilson 2013; Todorov 2017). The effects of facial appearances on inferences are strong, regardless of whether they are valid or not. Observers often form impressions after minimal time exposure to human faces, and such perceptions have powerful effects on visual attention, trait inferences, social judgments, and social interactions (Bar, Neta, and Linz 2006; Todorov, Pakrashi, and Oosterhof 2009; Willis and Todorov 2006).[5]

An emerging literature finds a significant relation between face-based impressions of observers about the personality traits of market participants and measures of economic outcomes (see, for example, Duarte, Siegel and Young 2012; Graham, Harvey, and Puri 2016; Blankespoor et al. 2017). These studies often use human observers to extract impressions about one or a few trait dimensions. However, there is a multitude of traits that can affect the economic outcomes, and the impressions can be influenced by the individual raters' idiosyncratic preferences and biases that may not be generalizable to the broader population.

[5] A growing literature in cognitive psychology and neuroscience provide evidence that first impressions formed from facial appearances predict important numerous social outcomes such as judicial outcomes (Zebrowitz and McDonald 1991), online dating (Finkel,Eastwick Karney, Reis, and Sprecher 2012), teaching evaluations (Hamermesh and Parker 2005), and political election outcomes (Todorov, Mandisodza, Goren, and Hall 2005; Antonakis and Dalgas 2009; and Joo, Steen and Zhu 2015). See Hugenberg and Wilson (2013) and Todorov (2017) for reviews of the literatures.

This paper aims to broaden the scope of such analyses to study how impressions about analysts' traits that are formed from observing their faces affect their role in providing information to the capital markets. We take advantage of recent advances in cognition science that the myriad traits impressions that can be elicited from observing a face can be reduced to 13 most-common trait impressions,[6] and further that three principal factors – trustworthiness, attractiveness, and dominance can capture a substantial amount of the variation in these most-common trait impressions. Building on Sutherland et al., Vernon et al. (2014) develop a machine-learning (ML) automated method to extract the three trait impression factors from a face photo. This method first delineates important fiducial landmark-points of a face to a set of 65 physical facial attributes and then apply a neural network model to these attributes to calculate the three impression factor scores. Vernon et al. report that their machine-derived impression factors account for a substantial amount of the variation in the trait impressions from the human raters.

In this study, we obtain a sample of all US sell-side analysts who maintain a LinkedIn profile as of May 2018 and apply Vernon et al. (2014) ML model to the profile picture of each analyst to extract the three trait impression factors trustworthiness (*TRUST*), attractiveness (*ATTRACT*) and dominance (*DOM*).[7] We use these factors to study their associations with characteristics of the analyst outputs for firms they covered between January 1990 through December 2017. We examine forecast accuracy and report length for the characteristics of analyst outcomes, conference call participation and herding behavior for their interactions with management, stock return response to analyst forecast revisions for capital market consequence, and All-Star status for labor market consequence.

[6] The 13 most common impressions culled from among a myriad number of impressions that are elicited from observing faces include aggression, approachability, trustworthiness, smile, confidence, health, attractiveness, age, babyfacedness, dominance, sexual dimorphism, intelligence, skin.

[7] See details in Appendix B.

The Vernon et al. (2014) automated method enables us to study a much larger sample of analyst face photos than would have been feasible with a more costly alternative method of using human raters to rate all photos. Furthermore, the Vernon et al. model is trained using an extensive database (1,000) of highly variable face photos that have been previously human-rated for a variety of impressions on social traits, and so are not specific to the face photos in our sample of analysts. The automated method removes potential researcher bias, though of course, the AI algorithms still reflect human biases from the training samples.

There are several reasons why studying financial analysts can be particularly informative and fruitful for understanding the role of face-based trait impressions on the capital markets. Financial analysts, as infomediaries in the capital markets, obtain private information from their professional network, including managers of the corporations they cover, and interpret their private and public information to produce outputs such as earnings forecasts and reports for their clients.[8] How well analysts do their jobs depends on their skill in extracting information from others, and in evaluating the information they obtain. The ability to extract information depends in part on how they are perceived in their social interactions with those who may have potential private information to share with them about the company they cover.[9] We can measure the quantity and quality of these analyst outputs to test how impressions of them from their social interactions affect analyst outputs. The report length measures the amount of effort expended, and forecast accuracy measures quality. How analysts are perceived by other market participants has consequences for their careers. Thus, we examine the association of the trait impression factors to the likelihood of

[8] See Kothari, So, and Rodrigo (2016) for a review on the literature on sell-side analysts' forecasts and their implications for asset pricing.

[9] Several papers highlight the importance of social interaction for financial analysts. For example, Soltes (2014) shows analysts acquire information from private meetings with management, Bradshaw (2012), Ke et al. (2006) and Brown et al. (2015) document that "access to management" is an important channel for analysts to gather information. Chen et al. (2018) find that analysts sharing the same office with local peers produce more accurate earnings forecasts and generate stronger stock market responses.

All-Star membership. Finally, how clients respond to the analyst output depends on the impression formed by clients about the analysts.[10] Analysts who are perceived by clients to be competent, honest, and likable are more likely to have their information be believed by clients. Therefore, we examine the association of the trait impression factors with abnormal stock returns.

In the first set of tests on the association of the trait impression factors and measures of analysts' research output, we find that *TRUST* and *DOM* are positively and significantly associated with both the quality and quantity of analysts' information provision outputs. We show that analysts with the highest *TRUST* and *DOM* scores produce earnings forecasts that are 2.59% and 5.56% more accurate than those with the lowest scores, respectively. In the cross-sectional tests, we find that the sensitivity of forecast accuracy to *TRUST* is higher in firms with higher earnings volatility. In the tests on analyst effort, we find that analysts with the highest *TRUST* and *DOM* scores produce longer reports relative to analysts with the lowest scores, by 17.72% and 17.56% more pages per firm-year, respectively. These results suggest that face-based trait impressions correspond to analysts' information acquisition intensity and effectiveness, and that the image of trustworthiness is more valuable when fundamental uncertainty is high.

Next, we examine analysts' social interaction characteristics: their tendency to ask questions in conference calls and their propensity to herd towards the guidance forecasts provided by the manager of the firms they cover. We show that analysts with the highest *DOM* are 53.52% more likely to ask questions in conference calls than analysts with the lowest *DOM* scores. On the other hand, analysts with a high *TRUST* score are 3.43% more likely to herd by making forecasts closer to the managerial guidance forecast than analysts with low *TRUST* scores.

[10] For example, Brownlow and Zebrowitz (1990) finds that facial appearance of television spokesperson affects the audience's perception of information quality. Gheorghiua et al. (2017) find that facial appearance of scientists affects the communication of scientific findings to the public through two key channels - selection (which research the public chooses to find out about) and evaluation (the opinions they form about that research).

These results, together with the earlier finding that *DOM* and *TRUST* are positively related to forecast accuracy, suggest that high *DOM* analysts may have a greater ability to extract useful information for their forecasts from asking managers in a public information environment. In contrast, high *TRUST* analysts may be rewarded by a greater willingness of managers to share relevant information with those they perceive to be more trustworthy.

In the tests relating trait factors with social learning, we find that *ATTRACT* is positively associated with forecast accuracy for junior analysts but is insignificant for senior analysts. On the other hand, *DOM* and *TRUST* are significant for both junior and senior analysts. These results suggest that impressions associated with attractiveness tend to be short-lived and become less important over a longer-term relationship. In contrast, trait impressions associated with dominance and trustworthiness have long-lasting effects.

To examine regulation's role on the impact of trait inferences, we focus on Regulation Fair Disclosure (Reg FD), introduced in October 2000 by the Securities and Exchange Commission to reduce selective disclosure by public companies. We find that *ATTRACT* is positively associated with forecast accuracy in the pre-Reg FD period but is insignificant post-Reg FD. This finding suggests that analysts with high *ATTRACT* scores enjoy greater access to insider information in the pre-Reg FD period. Under this interpretation, after the regulation change that leveled the playfield for information access, *ATTRACT* lost its advantage. Instead, *DOM* and *TRUST* become more valuable in analysts' information acquisition under the new regulatory environment.

We also find that gender modulates the effects of trait impression factors. Since the pioneering study of Becker (1971) on the economics of discrimination, a growing literature has begun to examine gender discrimination issues in the corporate world.[11] We analyze whether the

[11]Goldin and Rouse (2000) examine hiring discriminations against women. Bertrand, Goldin and Katz (2010) analyze the differences in career dynamics between female and male MBA graduates. Heilman (2012) describes how gender

effects of face-based trait inferences vary across female and male analysts. We find that while *DOM* is associated with greater forecast accuracy for male analysts, it is associated with *lower* accuracy for female analysts, despite the higher accuracy for the average female analyst than the average male analyst. This seems to suggest that societal norms do discriminate against women exhibiting behaviors associated with the dominance trait that facilitate information acquisition.

Our test has so far established that face-based trait impressions are substantially associated with analyst performance. This raises the question of whether such effects have consequences for the capital market and the analyst labor market. For the stock market reaction to analysts' earnings forecasts, we find that that stock prices react more strongly to forecasts issued by analysts with higher *TRUST* and *DOM* scores, incremental to other measures, including analyst skills. The 2-day return response to a one-standard-deviation increase in earnings forecast revision is 23 and 38 basis points higher if issued by an analyst with the highest *TRUST* and *DOM* scores relative to one with the lowest scores. The effects are mostly driven by male analysts and are not significant for the female subsample. Overall, our results indicate that trait impression factors play an important role in how financial analysts influence equilibrium asset prices.

We measure an analyst's career outcomes based on whether the analyst is recognized as an "All-Star Analyst" by *Institutional Investor* magazine (see, for example, Groysberg et al. 2011; Fang and Huang 2017). We show that, even after controlling for forecast accuracy and other analyst and brokerage characteristics, *DOM* increases the All-Star probability for male analysts by 19% for the highest *DOM* score relative to the lowest scores. In contrast, for female analysts, *DOM*

stereotypes lead to biased evaluative judgments and discriminatory treatment of women in work places. Bigelow, et al. (2014) show, in an experimental setting, that subjects consider IPOs led by female founders as less attractive. Newton and Simutin (2015) document the wage inequality between genders. Adams and Kirchmaier (2016) document the low female presence on corporate boards. Niessen-Ruenzi and Ruenzi (2018) find that female-managed funds attract significantly lower inflows than their male peers, despite of similarities in performance.

reduces their All-Star likelihood by a whopping 74% for the highest *DOM* score relative to the lowest score.

This evidence is consistent with previous research showing that women are stereotypically expected to portray warmth, empathy, and altruism, more so than men (Kite, Deaux, and Haines 2008; Ellemers 2018; Bordalo et al. 2019). Our finding of a "penalty" for women whose faces correspond to the impression of dominance or aggressiveness suggests that gender stereotypes in the market of sell-side financial analysts may have real performance and career consequences. Our results also indicate that incremental to objective measures of ability, All-Star membership may indeed be a popularity contest (Emery and Li 2009) from which dominant-looking males benefit.

We take several measures to verify whether these findings are robust. First, as shown in Jia et al. (2014) and He et al. (2019), a physical facial trait, the Facial Width-to-Height Ratio (*fWHR*), is associated with financial misreporting by male CEOs and forecast accuracy of Chinese male analysts. We control for *fWHR* in our analysis and confirm that *fWHR* is positive and significantly related to forecast accuracy. More importantly, for the purposes of this study, we find that our trait impression factors remain both economically and statistically significant, consistent with their capturing important dimensions of face-based impressions beyond the effect of *fWHR*.

Second, we explore whether omitted industry factors or other variables may drive the results. Such missing variables may influence the matching of certain types of analysts to a particular industry or how trait perceptions have a differential impact across genders. To address this possibility, we construct industry- and gender-adjusted trait factors and perform the analysis in a within-industry setting. Third, we control for a rich set of firm-, brokerage house-, and analyst characteristics, industry and year fixed effects. Fourth, we assess the likelihood that a profile picture is modified by editing software and show that the results remain similar after removing observations with high photo-editing probability. Lastly, we consider the possibility that specific brokerage houses are more likely to hire analysts with certain facial trait impressions or that the impact of trait impression factors can be age-dependent in a non-monotonic way. We include brokerage and age fixed effects and find the results to be robust.

Overall, these findings show that the face-based trait impression factors are associated with essential measures of analysts' performance, as well as stock prices and career outcomes. The evidence further suggests that the effects of the impression factors are at least in part associated with human and societal biases. In particular, the distinctly different *DOM* effect on female versus male analyst career outcomes suggests a form of gender discrimination in the financial analyst labor market. Some of the effects of the trait factors are short-lived, such as the attractiveness factor, and are mitigated through the building of a longer relationship and through disclosure regulation such as Reg FD. The effects of other traits tend to persist for longer.

Our study contributes to several strands of literature. A growing literature in economics, finance, and accounting documents the importance of face-based inferences.[12] Previous studies have demonstrated the effect of perceived competence or look of confidence in CEO selection and compensation (Graham, Harvey, and Puri 2016), IPO pricing (Blankespoor et al. 2017), mutual fund performance (Bai et al. 2019), financing to entrepreneurs (Huang et al. 2019). Cao et al. (2020) and Li et al. (2020) find a positive association between the attractiveness of Chinese analysts with their performance, whereas Li et al. (2020) document a beauty penalty for the US analysts. Our ML-based approach has the advantage that we can examine a large sample of

[12] Other papers have associated first impressions with wage setting (Hamermesh and Biddle 1994; Mobius and Rosenblat 2006), corporate career path (Linke, Saribay, and Kleisner 2016), law firm profitability (Biddle and Hamermesh 1998; Rule and Ambady 2010, 2011), and audit fee setting (Hsieh et al. 2019).

analysts for a more complete examination of how multiple trait impression dimensions affect economic activities.

Our systematic analysis using ML-based trait impression measures is especially relevant in the current environment where AI usage has become more pervasive. Major corporations are increasingly adopting face-scanning and ML technologies to identify character traits for important human resource decisions.[13] Proponents of such technology argue that its use helps reduce individual decision-makers' biases. On the other hand, critics suggest that the algorithms are opaque and AI algorithms developed by humans and trained using data based on the historical decisions and human actions reflect or even reinforce biases (Harwell 2019). Capital market participants need to understand the nature of the information that AI extracts and its consequences.

Our study also contributes to the literature on the determinants of sell-side analyst performance and the capital market consequences of analyst outputs.[14] In particular, Brown et al. (2015) provide survey evidence that private communications between analysts and management are more useful for analysts than their independent research. We add to this literature by showing that face-based trait impressions are relevant to their social interactions, and affect performance and career outcomes.

More broadly, our paper joins the emerging literature on the relevance and importance of social cognition and social interactions in economic decision making (see, for example, Duflo and Saez 2003; Shive 2010, Kaustia and Knüpfer 2012; Shiller 2000, 2017; Hirshleifer 2020). Drawing from social psychology (Schneider 2004), Bordalo, Coman, Gennaioli, and Shleifer (2016, 2019)

[13] As of October 2019, more than 100 employers, including Hilton and Unilever, now use a proprietary AI-driven interview assessment system developed by HireVue, and more than a million job seekers have been analyzed.

[14] This literature has shown the relevance of analyst experience, political views, portfolio complexity, the prestige of their brokerage house, and their industry experience for their performance (Clement 1999; Gilson et al. 2001; Malloy 2005; Kumar 2010; Gunn 2013; O'Brien and Tan 2015; Jiang, Kumar, and Law 2016; Bradley et al. 2017; and Merkley et al. 2020). Womack (1996) document significant market reactions to analyst's recommendation revisions, and Hong, Lim, and Stein (2000) find that analyst firm-specific information explains price momentum.

propose a "social cognition approach" to model stereotypes and argue that beliefs respond to social stereotypes. Our findings show how trait inferences form, influence social interactions, affect economic outcomes, and differ by gender.

2. Data

Our sample consists of US sell-side analysts and the firms they cover in the merged CRSP/COMPUSTAT data from January 1990 through December 2017. We obtain quarterly EPS forecasts from I/B/E/S and stock price and firm characteristics from CRSP and COMPUSTAT. We identify the sell-side financial analysts responsible for the EPS forecasts using information from I/B/E/S and Thomson Reuters Investext. For each forecast, we use the I/B/E/S analyst identification number and detailed history recommendation file to obtain the analyst's last name and first initial. We find the analyst's full name and brokerage house affiliations from Thomson Reuters Investext.

We then extract the analyst's photograph and available characteristics from their LinkedIn profile page after a manual check that the full name and history of job titles and employer affiliations match with the Investext database. Of the 4,511 sell-side analysts covered in Thomson Reuter Investext during 1990-2017, 1,656 maintain a LinkedIn profile as of May 2018, and 795 posted a profile picture. Our final merged sample consists of 190,600 quarterly EPS forecasts and 5,712 analyst-year observations for 5,905 unique firms. Below we describe the key variables and controls used in our study. Appendix Table A1 provides the list of variables and the definitions.

2.1 Face-Based Trait Impression Factors

When exposed to a face, human observers can form judgments about a range of traits, including age, aggression, trustworthiness, confidence, intelligence, and dominance.[15] Extending Oosterhof and Todorov's (2008) seminal research, Sutherland et al. (2013) use a principal components analysis to extract three factors– trustworthiness, dominance, and attractiveness– that together capture 72% of the variation of the 13 first impressions[16] by observers of faces. The literature suggests that these factors are rooted in evolutionary survival (see, for example, Todorov 2008; Zebrowitz et al. 2010; Fink et al. 2007; Oosterhof and Todorov 2008). Trustworthiness is associated with the observer's perception of whether the observed has the intention to help or harm. Dominance is associated with the observer's perception of whether the observed has the ability to carry out the intended actions so that the observer can determine whether to approach or avoid the observed. Attractiveness is associated with perceptions about success in sexual mating and natural selection (Buss and Schmitt 1993; Little, Jones, and DeBruine 2011; Thornhill and Gangestad 1999).

Vernon et al. (2014) recommend a machine learning method that is scalable to allow obtaining these first impression factors for a much larger sample. They propose a linear neural network technique that they show outperforms various alternative ML techniques considered.[17] We first apply the Vernon et al. (2014) method to analysts' photos to extract raw factor scores (*TRUST_Raw*, *ATRACT_Raw*, *DOM_Raw*) for each analyst. We validate these scores for a random sample of 100 photos using Amazon Mechanical Turk human raters. We find high correlations

[15] See, for example, Boothroyd et al. (2007), Oosterhof and Todorov (2008), and Walker and Vetter (2009).
[16] The 13 first impressions are: Aggression, Approachability, Trustworthiness, Smile, Confidence, Health, Attractiveness, Age, Babyfacedness, Dominance, Sexual Dimorphism, Intelligence, Skin. The first factor (Trustworthiness) has highest loadings from approachability, trustworthiness, and degree of smile. The second factor (Attractiveness) has the highest loadings from attractiveness, health, and babyfacedness. The third factor (Dominance) has the highest loadings from dominance, sexual dimorphism, and confidence. See Sutherland et al. (2013) for details.
[17] Trained with a large sample of pictures of faces rated by human raters, Vernon et al. (2014) show that the algorithm-generated trait scores are highly correlated with those from human raters, with statistically significant average correlation coefficients equal to 0.9, 0.7, and 0.67 for trustworthiness, attractiveness, and dominance, respectively.

between the machine scores and human rater scores, with an average correlation of 80% across the three traits. Appendix B describes the detailed steps in our procedure to obtain these three factors for our sample of analyst face photos.

It is possible that there are omitted industry-level factors or other variables that affect the matching of certain types of analysts to particular industries. To address this, we transform the raw trait factor scores to obtain within-gender and within-industry rankings. Each year and for each 2-digit SIC industry, we sort analysts of the same gender by their corresponding trait scores and scale the relative trait factors between zero and one.[18] We define the adjusted trait factors as *TRUST*, *ATTRACT*, and *DOM*, respectively.

2.2 Analyst Activities and Performance

We characterize analysts' activities both at the forecast level and at the analyst-year level. For each forecast, we measure its accuracy (*ACCURACY*) as the negative proportional mean absolute forecast error (*PMAFE*) (see, for example, Clement 1999; Malloy 2005; De Franco and Zhou 2009; Green et al. 2014; and Bradley et al. 2017):

$$PMAFE_{ijt} = \frac{AFE_{ijt} - MAFE_{jt}}{MAFE_{jt}} \quad , \tag{1}$$

where AFE_{ijt}, the absolute forecast error of analyst *i* for firm *j* and quarter *t*, is the absolute difference between *i*'s forecast and the actual EPS, and $MAFE_{jt}$ is the corresponding firm-quarter mean of *AFE,* excluding *i*. In comparison with other measures of forecast errors, *PMAFE* controls for omitted firm-level and time-specific variation in forecast accuracy, thereby providing better identification. To assess an analyst's tendency to herd with the forecasts of firm managers, we

[18] We use the following transformation for each trait factor: (trait-min)/(max-min), where min and max are the minimum and maximum values of the corresponding trait factors across analysts covering the same industry for a given year.

compare the analyst's forecast with the most recent management forecast. We define *HERD* as equal to one if the difference is within one cent and zero otherwise (Bagnoli et al. 2008).

At the analyst-year level, we measure an analyst's research outputs for a given firm with *PAGES*, defined as the logarithm of the number of pages of reports the analyst provides. We obtain page counts from the Thomson Reuters Investext database and exclude non-essential contents such as disclaimer, legal notice, and brokerage information. In addition, using over 200,000 conference call transcripts from SeekingAlpha.com from 2000 through 2017, we define *CALLS* as the logarithm of one plus the number of conference calls during which an analyst asked at least one question for a year. We capture analyst career outcomes by manually collecting the list of All-Star Analysts from Institutional Investor magazine from 1991 to 2017 and matching with our sample by analyst name and brokerage affiliations. We define I_{STAR} as one if an analyst obtains the All-Star status, and zero otherwise.

2.3 Control Variables

We include a rich list of control variables that capture analyst, firm, and brokerage house characteristics that may also influence analysts' performance. Using information from LinkedIn, we identify the year an analyst started college and determine the analyst's birth year by assuming that the analyst began college at the age of nineteen.[19] We use an analyst's first name and the "Behind the Name" database to obtain the analyst's gender *(GENDER)*[20] We follow Lefevre et al. (2013) and use profile pictures to obtain facial width-to-height ratio *(fWHR)*.[21]

[19] Based on the National Center for Education Statistics (https://nces.ed.gov/fastfacts) from 1970 through 2017, 53% to 69% of students enrolled in full-time degree-granting postsecondary institutions are between ages 18 to 21.

[20] The site https://www.behindthename.com collects the gender and name usage history from various sources including the Social Security Administration (SSA). Of the 795 analysts in our sample, 3 have unisex first names and 45 correspond to names not included in the "Behind the Name" database. For these 48 analysts, we determine the gender using FaceX's face analytics API (https://facex.io/). This procedure classifies the 48 analysts as 46 males and 2 females with a confidence of 99.3% or higher.

[21] Specifically, *fWHR* is the distance between the left and right zygion relative to the distance between the upper lip

The next set of variables are measured at the analyst-year level. I_{JUNIOR} is an indicator variable taking a value of 1 if an analyst is within the analyst's first two years following an industry and zero otherwise. *AGE* is an analyst's age, computed as the year of the observation minus the birth year. *MEAN_ERROR* is the average proportional mean absolute error of all forecasts issued by an analyst for the year. *PORTFOLIO_CAP* is the sum of the market capitalization of firms (in logarithms) covered by an analyst. *BROKER_SIZE* is the size of the brokerage house that an analyst is affiliated with, measured by the number of analysts it employs.

The next set of variables, which are measured at the forecast level, capture analyst and brokerage-house characteristics (Clement 1999; and Bradley et al. 2017). *TOP10* is an indicator variable that takes a value of one if an analyst is affiliated with a brokerage house that belongs to the top 10% of the distribution of the number of analysts employed, and zero otherwise. General experience *(GEXP)* and firm-specific experience *(FEXP)* are the numbers of years since an analyst appeared in I/B/E/S and from the analyst's first forecast of the firm, respectively. *SIC2* refers to the numbers of 2-digit SIC industries an analyst covers, and *HORIZON* is the number of days between the date when the forecast is issued and the earnings announcement date.

We adjust the above variables by subtracting the corresponding mean value across all analysts covering the firm over the same quarter to account for the possibility that other omitted firm-level factors that may drive our results (Clement 1999). We denote the corresponding adjusted variables *DAGE*, *DGEXP*, *DFEXP*, *DTOP10*, *DSIC2*, and *DHORIZON*.

We also control for variables that capture the firm's information environment. *FOLLOWING* is the number of analysts following the firm in the corresponding quarter. *SIZE* and *BM* refer to the logarithm of the market capitalization and book-to-market ratio of the firm,

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and the highest point of the eyelids. *fWHR*'s correlation coefficient with *TRUST*, *ATTRACT*, and *DOM* are 0.13, -0.08, and -0.10, respectively.

measured at the end of the month before the earnings forecast. Finally, *RET* is a firm's prior six-month cumulative returns minus the CRSP value-weighted returns.

We winsorize all continuous variables at the 1% and 99% levels to ensure that outliers do not unduly influence the results. Table 1 summarizes the main variables (Panel A) and the pairwise Pearson correlation matrix (Panel B). Panel A shows that, at the analyst level, mean raw traits scores are 0.21, 0.06, and 0.16 for *TRUST_Raw*, *ATTRACT_Raw,* and *DOM_Raw*, respectively, and with substantial variations across analysts. Out of the 795 analysts, 101 (or 13%) are female, who tend to have higher *TRUST_Raw* and *ATTRACT_Raw*, and lower *DOM_Raw* scores than their male peers.[22] Given the systematic differences in the raw values of trait factors across gender, and to account for the potential selection of certain analysts to a given industry, we use the gender- and industry-adjusted trait factors (*TRUST*, *ATTRACT*, and *DOM*) for our empirical analysis.

Table 1 Panel A also shows that, for a given year, an average analyst has a 7.64% probability of becoming an All-Star Analyst and participates in 13.3 (= $e^{2.59}$) conference calls. The analyst contributed 18.17 (= $e^{2.91}$) pages of reports, has a mean forecasts error of 0.57%, covers a portfolio with a total market capitalization of 5.3 (= $e^{15.48}$) billion USD, and is affiliated with a brokerage house with 73.68 analysts (*BROKER_SIZE*). At the forecast level. Panel A shows that an average forecast has an *ACCURACY* of 0.0174 and is 59.4% likely to herd with a firm manager (*HERD*). 45.2% of analyst-years observations are associated with junior analyst status *(I_{JUNIOR}).*[23] An average firm has an analyst coverage of 4.47 (*ANALYST_FOLLOWING*), a market capitalization of 2.65 (= $e^{14.79}$) billion USD, and a BM of 0.53.

[22] The percentage of female analysts in our sample is comparable to the survey results of Green et al. (2009), which shows that the representation of female sell-side analysts is between 14% to 16% of all analyst positions in the US between 1994 and 2005.
[23] Junior years mainly consist of the entry of new analysts into the profession, and the industry switching of existing analysts. The industry switching frequency is in line with the literature (e.g. Balashov 2017 documents that 3434 analysts made 4316 industry switches between 1984 and 2014).

Table 1 Panel B shows that facial trait factors tend to be correlated, consistent with people's tendency to form a holistic first impression when exposed to a face. Therefore we also consider an alternative set of trait factors orthogonalized to each other via the modified Gram–Schmidt process (Golub and VanLoan 1996).[24] In Section 7.1, we compare our sample's key characteristics with all LinkedIn analysts (including those without profile pictures) and the analysts covered in the I/B/E/S database. Additional summary statistics are presented in Appendix Table A2, in which we describe gender differences across key forecast-level variables and present correlation coefficients for the other variables.

3. Face-Based Trait Impressions and Analyst Performance

We investigate the relation between face-based trait impression factors with the quality and quantity of analyst outputs, and with the characteristics of the analysts' interactions with firm management.

3.1 Output Characteristics: Forecast Accuracy

We measure the quality of the information output produced by analysts as the EPS forecast accuracy to associate with the trait impression factors. We first present baseline analyses for the relationship between factors and forecast accuracy, and then investigate the cross-sectional effects on this relation by firm fundamental uncertainty, market learning about the analyst accuracy, and the regulatory disclosure regime.

3.1.1 Baseline Analyses

[24] We use the following orthogonalization order, from first to last: trustworthiness-attractiveness-dominance. We rescale the orthogonalized variables to be between zero and one. We obtain similar results when alternative ordering us used.

We regress an analyst's forecast accuracy (*ACCURACY*) on the analyst's trait factors using the following panel regression model and its nested forms:

$$ACCURACY_{i,j,k,t} = \beta_0 + \beta_1 Trait\ Factors + \gamma X + \varepsilon \ , \qquad (2)$$

where *TraitFactors* are *TRUST*, *DOM*, and *ATTRACT*, and *X* represents firm-, analyst- and brokerage-house- characteristics that may also be correlated with analyst forecast accuracy. *X* is a vector that includes: number of analysts following the firm (*ANALYST_FOLLOWING*), firm size (*SIZE*), book-to-market ratio (*BM*), and past returns (RET_{6M}), analyst age (*AGE*) and gender (I_{FEMALE}), Facial Width-to-Height Ratio *(fWHR)*, the top 10% brokerage house affiliation indicator (*DTOP10*), number of firms (*DPORTFOLIO_SIZE*) and industries (*DSIC2*) the analyst follows, forecast horizon (*DHORIZON*), analyst's general and firm-specific experience (*DGEXP* and *DFEXP*). We also include industry and year fixed effects and compute standard errors that are double clustered by firm and by analyst in all regressions, unless otherwise noted.

Table 2 reports the regression results. Columns (1) through (3) include the trait impression factors one at a time, and column (4) analyzes the effect of the face-based Width to Height ratio. Column (5) includes all three orthogonalized trait factors and *fWHR*. In column (6), we replace *fWHR* with an alternative measure that is gender- and industry- adjusted by ranking an analyst's *fWHR* among the analysts of the same gender following the same industry during the year. Overall, the results indicate that *TRUST* and *DOM* are positively and significantly related to accuracy, but *ATTRACT* is not.

We illustrate the economic magnitude of the effects using the coefficient estimates in column (5). The coefficients (in %) indicate that the forecasts of analysts with the highest *TRUST* and *DOM* scores are 2.59% and 5.56% more accurate than the ones with the lowest scores, respectively. This suggests that analysts with more trustworthy and dominant faces tend to have more accurate forecasts. These economic magnitudes are large and comparable with other major determinants of forecast accuracy documented in previous studies. For example, Bradley et al. (2017) find that analysts' prior experiences contribute to a 1.55% to 3.58% difference in forecast accuracy.

As for the control variables, the coefficient of *fWHR* is positive and significant, implying that forecasts issued by analysts with the highest *fWHR* score are 0.71% more accurate than those from analysts with the lowest *fWHR*, consistent with the finding of He et al. (2019). The coefficient of *FEMALE* is positive and significant, suggesting that the forecasts of female analysts are 2.41% more accurate than those of male analysts. The finding that female analysts have higher forecast accuracy is consistent with the self-selection argument by Kumar (2010). In the analyst labor market with perceived discrimination against females, only high ability female analysts self-select into the profession. [25]

The baseline results establish that trustworthy and dominant faces are positively associated with financial analysts' forecast accuracy. We next explore how the cross-sectional effects of trait impressions vary with firm fundamental uncertainty, market learning about an analyst's ability over time, and regulatory regime change with Reg FD governing how analysts interact with company managers.

3.1.2 Cross-Sectional Analyses

We examine how the relation between trait impression factors and forecast accuracy may vary depending on the fundamental uncertainty of the information environment and market

[25] The results for the other control variables show that accuracy increases with analysts' firm-specific experience (*DFEXP*) and portfolio size (*DPORTFOLIO_SIZE*) and decreases with forecast horizon (*DHORIZON*), consistent with Clement (1999) and Bradley et al. (2017). The coefficient on analysts' general experience (*GEXP*) and age (*AGE*) are negative and significant, likely because they are positively correlated with analysts' firm-specific experience (*DFEXP*), with correlation coefficients of 0.5 and 0.24, respectively.

learning from the history of analyst outcomes. When the information environment is more uncertain, we expect that traits related to analyst's ability to acquire information likely become more important for forecast accuracy. We proxy for environmental uncertainty using earnings volatility, measured as the standard deviation of seasonal earnings changes over the four years ending on the fiscal-end date (Thomas, 2002; Dichev and Tang 2009).

We define I_{HighEV} as equal to one if earnings volatility is greater than the sample median, and zero otherwise. We re-estimate the previous regression and include the interaction of uncertainty binary variable with trait factors as below:

$$ACCURACY_{i,j,k,t} = \beta_0 + \beta_1 Trait\ Factors\ \times I_{HighEV} + \gamma\, X + \varepsilon, \tag{3}$$

where X includes all the control variables included in equation (2), as well as individual Trait Factors and I_{HighEV}.

Table 3 Panel A reports the regression results, with columns (1) through (3) include the trait factors one at a time, and column (4) consists of all orthogonalized trait factors. The key variable of interest is the interaction term $Trait\ Factors\ \times I_{HighEV}$. Results in column (4) show that the coefficients for the interaction of *TRUST* and I_{HighEV} is positive and significant, suggesting that the effect of *TRUST* on forecast accuracy is 2.81% higher for firms with high underlying uncertainty than firms with low uncertainty. The coefficient of *TRUST* is positive but no longer significant. In contrast, the interaction terms of *ATTRACT* and *DOM* with I_{HighEV} are not statistically significant, but *DOM*'s coefficients remain positive and significant. These results suggest that trustworthiness is a more valuable trait factor for analysts covering firms facing more significant fundamental uncertainty, whereas the effect of *DOM* is strong for both low- and high-uncertainty firms.

Face-based impressions may be most relevant for initial encounters but are likely to weaken over time after the market is able to learn about analyst ability from their actual history of outcomes. Thus, if face-based impressions mostly correspond to intuitive, short-term perceptions, we expect the effect of traits to be weaker for senior analysts than for junior analysts. On the other hand, if the trait factors are related to how effectively the analyst interacts with providers of information, face-based impressions that facilitate long-term relationship building through interpersonal interactions and become more important over time.

To test the effect of facial traits throughout an analyst's career, we classify analysts into two groups, senior and junior. We define an indicator variable, I_{JUNIOR}, that takes a value of one if an analyst's industry experience is two years or less and zero otherwise.[26] We estimate the following panel regression model:

$$ACCURACY_{i,j,k,t} = \beta_0 + \beta_1 Trait\ Factors\ + \beta_2 Trait\ Factors\ I_{JUNIOR} + \gamma X + \varepsilon, \qquad (4)$$

where X includes all the control variables included in equation (2) and I_{JUNIOR}. Coefficient β_1 capture the effect of traits on forecast accuracy for senior analysts, and β_2 captures the additional effect for junior analysts.

Table 3 Panel B reports the regression results, with columns (1) through (3) including the trait factors singly, and column (4) including all orthogonalized trait factors. The coefficient on *ATTRACT* is insignificant, but the coefficient on the interaction term of $ATTRACT \times I_{Junior}$ is positive and significant. These results suggest that there is a beauty premium for junior analysts but not senior analysts. Attractiveness tends to be important for junior analysts about whom uncertainty about skill is high. As the market observes an analyst's track record and learns directly about the analyst's ability, they become less influenced by beautiful faces. This result suggests that

[26] Results are robust if we include the first three years of the analyst's experience.

attractiveness may give junior analysts advantages in information access, consistent with a beauty premium in the labor market (see, for example, Mobius and Rosenblat 2006; Andreoni and Petrie 2008; and Cao et al. 2020).

In contrast, the coefficient for *TRUST* and *DOM* remains positive and significant, confirming our baseline results and suggesting that the effects of these two trait factors are present for both junior and senior analysts. Furthermore, the coefficients of $I_{junior}TRUST$ and $I_{junior}DOM$ are insignificant, suggesting that the influence of these two traits does not vary significantly with an analyst's industry experience.

Together, these evidence indicates that the effects of perceived beauty are likely short-term and are mitigated by market learning about experienced analysts; see also Section 4. In contrast, perceived trustworthiness and dominance remain important even for experienced analysts, possibly because these factors are associated with interpersonal skills and the ability to obtain information from other market participants.

3.1.3 Regulation Fair Disclosure

We next study the role of the regulatory environment on trait factor-accuracy relation. Disclosure regulations affect when and how analysts communicate with firm managers. On October 23, 2000, the Securities and Exchange Commission implemented Regulation Fair Disclosure (Reg FD) to prevent selective disclosure of private information by public companies. Several papers document that Reg FD has leveled the playing field among sell-side analysts by curbing the passage of private information from managers to analysts (e.g., Cohen et al. 2010; Tang 2013). We hypothesize that if a trait factor contributes to better access to private information from company executives, its effect would be weaker in the post-Reg FD period when equal access is required by law.

We divide our sample into pre-Reg FD and post-Reg FD periods and estimate equation (2) for each period. Table 4 presents the results, with columns (1) and (2) corresponding to the pre- and post-Reg FD periods, respectively. The results indicate that the key independent variables *TRUST* and *DOM* are significantly positive for the post-Reg-FD period, but not for the pre-Reg-FD period. On the other hand, *ATTRACT* is only significant in the pre-Reg FD period. In the pre-Reg-FD period, forecasts issued by the analysts with the highest *ATTRACT* scores are 5.54% more accurate than those from the analysts with the least scores. For the post-Reg-FD period, analysts with the highest *TRUST* and *DOM* scores have accuracies that are 3.00% and 5.64% higher than those with the lowest scores.

These findings suggest that in the pre-Reg FD era, when access to insiders for private information may have a first-order effect on forecast accuracy, sell-side analysts' attractiveness is crucial for obtaining access. In the post-Reg FD era, when there is a level-playing field for access to management information, trustworthiness and dominance factors become more important for accuracy. Recall that the factor scores are within-gender scores. Interestingly, the coefficient of I_{FEMALE} is insignificant for the pre-Reg FD period but is significant post-Reg FD. This suggests that the importance and relevance of trait factors for accuracy may operate differently in male versus female gender groups. We explore this further in Section 4, where we study the female analyst sample separately.

3.2 Output Characteristics: Report Length

We next analyze a quantitative measure of analysts' research output—the number of pages their reports contain. A more extended report potentially allows an analyst to provide more comprehensive discussions of additional information such as longer-term growth forecasts and the uncertainty that a firm faces.

We analyze the effect of trait impression factors on report length by estimating the following regression model at the analyst-firm-year level:

$$PAGES_{i.j.t} = \beta_0 + \beta_1 Facial\ Traits + \gamma X + \varepsilon \quad (5)$$

where *PAGES* is the natural logarithm of the number of pages of reports an analyst provides for a given firm-year and *Facial Traits* include *TRUST*, *DOM*, and *ATTRACT*. *X* corresponds to most of the firm, analyst and brokerage-house characteristics listed in equation (2), measured annually for the preceding year.[27] We also include the analyst's preceding-year forecast accuracy (*MEAN_ERROR*) and the total market value and average book-to-market ratios of firms that the analyst covers (*PORTFOLIO_CAP*, and *MEAN_BM*). In addition, we include firm and year fixed effects to account for additional omitted characteristics and compute standard errors that are double clustered by firm and by year.

Table 5 reports the results, with columns (1) through (3) include trait factors one at a time, and column (4) has all three orthogonalized factors. The result shows that analysts with the highest *TRUST* and *DOM* scores also provide substantially longer reports per year. Economically, given the mean *PAGES* value of 2.91, column (4) shows that analysts with the highest *TRUST* and *DOM* scores provide an extra number of 3.24 (= $e^{2.91+0.1633}$- $e^{2.91}$) and 3.21 (= $e^{2.91+0.1618}$- $e^{2.91}$) pages per year for a firm than analysts with the lowest scores, an increase of 17.72% and 17.56% relative to the mean of 18.28 (=$e^{2.91}$) pages, respectively.[28] These results corroborate our earlier finding that analysts with higher *TRUST* and *DOM* scores produce more accurate forecasts. Together, the

[27] Specifically, we include *ANALYST_FOLLOWING, SIZE, BM,* RET_{6M}, *AGE,* I_{FEMALE}, *fWHR, TOP10, PORTFOLIO_SIZE, SIC2, GEXP*, and *FEXP*. We do not include the forecast-specific variable, *HORIZON*. We replace *TOP10* with the more granular brokerage house size variable *BROKER_SIZE* following Bradley et al. (2017). The results remain similar when we use *TOP10*.

[28] After removing disclaimer, legal notices, and contact information, the average length per report is 7.1 pages, consistent with Huang et al. (2014). An analyst issues an average of 2.6 reports per firm year.

evidence shows that the two trait factors enhance both the quality and quantity of analysts' research outputs.

3.3 Interaction Characteristics: Conference Call Participation and Herding

We next examine how face-based trait impressions affect information acquisition by analysts through interactions with the management in conference calls. We also examine another analyst social behavior, herding upon the forecasts of firm managers.

Conference calls are an important public information disclosure channel of a company and a valuable opportunity for analysts to access firm management. Managers permit only a limited number of questions in conference calls and have discretion in selecting questions (e.g., Mayew 2008). Trait impressions may help an analyst establish a long-term relationship with firm managers through in-person settings such as investor days and company site visits (e.g., Kirk and Markov 2016; Cheng et al. 2016; Wu and Yaron 2018; Dong et al. 2019). Consequently, the analyst-manager relationship can affect an analyst's opportunity to ask questions. As shown by Mayew, Sharp, and Venkatachalam (2013), these opportunities are valuable—a skillful analyst can obtain signals that complement the analyst's analysis or prior information, allowing the analyst to gain an informational advantage.[29] We therefore test whether analysts' trait impressions affect the probability that an analyst's questions are addressed in conference calls.

To do so, we estimate the following regression model using analyst-year observations:

$$CALLS_{i,t} = \beta_0 + \beta_1 Trait\ Factors + \gamma X + \varepsilon, \tag{6}$$

where *CALLS* is the logarithm of one plus the number of conference calls during which an analyst asked at least one question for the year. *Trait Factors* include the orthogonalized factors: *TRUST*,

[29] Favoritism toward an analyst in allowing analyst questions may also be correlated with the firm dropping hints to the analyst in unrecorded informal communications.

DOM, and *ATTRACT*. *X* includes all the control variables included in equation (5). In addition, we follow Mayew (2008) and include *FORECAST_FREQ*, the number of EPS forecasts an analyst issues for the firm in the preceding year.

Table 6 presents the results, with columns (1) through (3) includes trait factors one at a time, and column (4) includes all three orthogonalized factors. Column (4) indicates that analysts with higher *DOM* scores have more opportunity to have their questions addressed during conference calls. Economically, given the mean *CALLS* value of 2.59, column 4 indicates that analysts with the highest *DOM* scores actively participates in an extra number of 7.14(= $e^{2.59 + 0.4287}$ - $e^{2.59}$) conference calls per year than analysts with the lowest scores, an increase of 53.52% relative to the mean of 13.34 (= $e^{2.59}$). Because the appearance of dominance is associated with the impression of confidence and competence, managers likely perceive analysts with dominance traits as more capable and confident, and therefore respond by giving them more opportunities to ask questions.

The second dimension in our characterization of the analyst-manager interactions is herding, defined as an analyst's tendency to overweight signals from firm managers when making earnings forecasts or recommendation revisions (e.g., Welch 2000; Cotter et al. 2010).

We define herding (*HERD*) more specifically to equal one if the absolute value of the difference between an analyst forecast and management guidance (the most recent analyst forecast) is less than or equal to 1 cent and zero otherwise. We then estimate the following logit regression for analyst-firm-year observations:

$$HERD_{i,j,t} = \beta_0 + \beta_1 \times Facial\ Traits + \gamma \times X + \varepsilon, \qquad (7)$$

where facial traits include *TRUST*, *DOM*, and *ATTRACT*. *X* corresponds to the firm-, analyst- and brokerage-house- characteristics listed in equation (2), measured annually for the preceding year.

Table 6, columns (5) through (8) present the results, with columns (5)-(7) includes trait factors one at a time, and column (8) includes all three orthogonalized factors. Column (8) indicates that the coefficient of *TRUST* is positive and significant, at 0.14. Economically, analysts with the highest *TRUST* scores is 3.43% more likely to herd with managers than analysts with the lowest scores—a 5.77% increase relative to the mean herding probability of 59.40%.

In sum, our results suggest that the appearance of dominance may give such analysts better opportunities to extract information from managers in conference calls. On the other hand, although the more trustworthy-looking analysts tend to be more credulous, they may maintain good relationships with the managers and in turn are rewarded with better access to information. These results indicate the multifaceted channels through which trait impressions influence information acquisition.

4 Trait Factors and Analyst Performances—the Role of Gender

Studies in psychology show that gender plays a vital role in the communications process. Females and males are usually perceived differently during interpersonal interactions due to gender stereotypes shaped by cultural backgrounds and social norms. For example, Mast and Kadji (2018) show that during physician-patient communications, patients are more satisfied when female physicians are perceived as less dominant (e.g., softer voice, less expansive posture), but the effect was opposite for male physicians: patients are more satisfied when male physician behave more dominantly. Biddle and Hamermesh (1998) show that physically more attractive male attorneys obtain higher raises, whereas there is no significant effect for female attorneys. Therefore, the relation between impressions of traits and analyst performance may also differ by gender.

We aim to gain insight into this important question by examining whether trait factors' influence on performance measures differs by gender. Female analysts account for 12.7% of all analysts in our sample. Table 1, Panel A reveals gender differences in trait impression scores. Female analysts tend to be perceived as more trustworthy, more attractive, and less dominant. To account for the cross-gender differences in the trait factor scores and focus on within-gender differences, we examine performance measures for the female-only sample and report the results in Table 7. Columns (1) through (4) correspond to regression specifications where the dependent variables are forecast accuracy, report length, conference call participation, and herding.

Column (1) indicates that the coefficients of *ATTRACT* and *DOM* are negative and significant, and that of *TRUST* is insignificant. Even though female analysts issue more accurate forecasts on average, there is a negative association between the trait perception of attractiveness and dominance and forecast accuracy. This pattern is in sharp contrast with the finding of a *positive* relation between *TRUST* and *DOM* with forecast accuracy in the full sample that is 87% comprised of male analysts

These results are consistent with the psychology literature, which finds perceived aggressiveness (one key component of the dominance trait) causes a more significant disadvantage for females (e.g., Heilman 2012) than for males due to traditional gender norms. In other words, firms may be less willing to share information with female analysts that are perceived to be dominant, as compared with male analysts that are perceived to be dominant. Furthermore, female analysts who are perceived to be attractive may also be perceived to be inexperienced and immature, hindering their ability to gather information through interactions with management.

In terms of social interaction characteristics, column (2) shows that *DOM*'s coefficient is positive and significant, suggesting that, similar to male analysts, dominant-looking female analysts also have more opportunities to ask questions during conference calls than the less dominant-looking females. As for female analysts' report lengths and tendency to herd with the management, columns (3) and (4) do not show any significant association between impressions of traits and herding tendencies.

5. Capital and Labor Market Outcomes

Our analysis so far has have established an association between face-based trait impressions and analysts' performance that is both statistically significant and economically substantial. This raises the question of whether these effects have capital market or labor market consequences. We next examine effects upon stock prices and career outcomes for analysts.

5.1 Capital Market Implications

We first investigate whether analysts' trait impressions modulate the stock market responsiveness to analysts' earnings forecast revisions. We calculate the two-day cumulated abnormal return CAR (0,1) as the difference between the buy and hold individual stock return and the CRSP value-weighted index return around the forecast release day. We follow Clement et al. (2003) to exclude days with multiple forecasts or days of earnings announcements to rule out confounding events that may also affect stock returns.

We estimate the following panel regression model:

$$CAR_{i,j,t} = \beta_0 + \beta_1 REVISION + \beta_2 Trait\ Factors \times REVISION + \gamma X + \varepsilon, \qquad (8)$$

where *Facial Traits* include *TRUST*, *DOM*, and *ATTRACT*. *REVISION* is an analyst's EPS forecast minus the rolling consensus EPS. *X* includes analyst- and brokerage house-characteristics measured over the prior year: the control variables included in equation (2), individual Trait Factors, *fWHR*, and *fWHR*REVISION*. In addition, we follow Clement and Tse (2003) and measure analyst firm-specific skill with *LAG_ACCURACY*, defined as the average forecast accuracy of the analyst for the firm over the prior eight quarters. We include *LAG_ACCURACY* and its interactions with *REVISION*. We also have firm and year fixed effects and compute standard errors that are double clustered by firm and by analyst. The interaction term *REVISION*LAG_ACCURACY* accounts for the role of analyst skill on price responsiveness. Therefore, the term *REVISION*TraitFactors* captures the influence of facial traits on price responsiveness incremental to the effect of measurable skills.[30]

Table 8 reports the results. Column (1) presents the benchmark case and shows that the coefficient on *REVISION* is positive and significant, consistent with the previous literature (see, for example, Park and Stice 2000). Column (2) incorporates the trait impression factors and shows that *TRUST*REVISION* and *DOM*REVISION* are positive and statistically significant. This indicates that the market reacts more strongly to revisions issued by analysts who appear to be more dominant and trustworthy, even after controlling analyst skills. In terms of economic magnitude, a one standard deviation increase in EPS revisions issued by analysts with the highest *TRUST* and *DOM* scores generates abnormal returns that are 23 and 38 basis points higher than revisions issued by analysts with the lowest scores, respectively.[31]

As a benchmark for comparison, a one-standard-deviation change in the EPS forecast revisions by the analyst in the highest *LAG_ACCURACY* decile is associated with 74 bps higher abnormal returns compared to revisions issued by the analysts in the lowest decile.[32] This

[30] This inclusion also helps account for the possibility that trait impression factors may affect earnings responsiveness indirectly through their impact on analysts' past performances. For example, given our earlier findings that *DOM* and *TRUST* are positively associated with analyst forecast accuracy, investors might recognize the skills of analysts and hence respond more strongly to forecasts issued by those with high skills. Therefore If investors are only responding to analyst skills but not the trait perception factors, the inclusion of *LAG_ACCURACY*REVISION* would subsume the explanatory power of *TRAITS*REVISION*.

[31] The standard deviation of EPS revisions is 0.2121. For *TRUST* and *DOM*, the economic magnitude in CAR (in %) is calculated as 1.0805*0.2121=0.23 and 1.7744*0.2121=0.38, respectively

[32] The economic magnitude is computed as 1.8919*0.2121*1.85, where 1.85 is the difference between the top and

comparison indicates that trait impressions have an influence that is economically substantial in explaining price reactions.

Columns (3) and (4) report the coefficient estimates for the male and female subsamples, respectively. Column (3) shows that, among the male analyst, *TRUST*REVISION* remains positive and highly significant. *DOM*REVISION* is still positive, although the statistical significance is weaker, with a t-stat of 1.54. Similarly, *LAG_ACCURACY*REVISION* also remains positive, but it is now statistically insignificant. This reduction in statistical significance relative to the full sample could derive from either a smaller sample size, or from the lower importance of these two factors for the male analysts. For female analysts, column (4) shows no significant relations between facial traits and market reactions. The female coefficient of *LAG_ACCURACY*REVISION* is substantially larger than its value for the full sample or the male sample, suggesting that investors' responses to female analysts' forecasts are highly dependent on their skills.

Overall, these findings indicate that the stock market reacts more strongly to forecasts issued by male analysts who look more trustworthy and, to a lesser extent, more dominant. So face impressions are relevant for market price setting. In addition, while the market does not seem to rely heavily on male analysts' past forecast accuracy when evaluating their forecasts, all else equal, it does for female analysts. This is a novel finding that is of interest for future exploration.

5.2 Labor Market Outcomes

We next turn to labor market implications. We measure an analyst's career path by identifying whether the analyst obtains the All-Star status. Every year, *Institutional Investor* magazine organizes an All-Star Analyst selection by surveying asset managers and buy-side

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bottom quintile values of *LAG_ACCURACY*.

analysts. Being selected as an All-Star Analyst indicates a successful career for the sell-side analyst as it brings significant increases in coverage, clients, and compensation (Groysberg et al. 2011).

We investigate whether an analyst's trait impressions affect the analyst's probability of obtaining the All-Star status by estimating the following analyst-year logistic regression:

$$(I_{STAR})_{i,t} = \beta_0 + \beta_1 Facial\ Traits_{t-1} + \beta_2 X + \varepsilon, \quad (9)$$

where I_{STAR} is the All-Star status indicator, *X* includes the following control variables measured at the prior year: the analyst's prior year All-Star status (*LAG_STAR*), *Facial Traits* include *TRUST*, *DOM*, and *ATTRACT*. Following Bradley et al. (2017), *X* includes the following analyst- and brokerage house-characteristics, measured over the prior year: analyst age (*AGE*), mean forecast error (*MEAN _ERROR*), the number and total market value of firms, and the number of industries covered by the analyst (*PORTFOLIO_SIZE*, *PORTFOLIO_CAP*, *SIC2*), and the size of the brokerage house that the analyst is affiliated with (*BROKER_SIZE*). We also include year-fixed effects. To better understand the role of gender in analyst career successes, we estimate the regression for the male and female analyst subsample separately.

Table 9 presents the results. Column (1) shows that the coefficient of *DOM* is positive and significant for male analysts. In terms of economic magnitude, the All-Star probability for a male analyst with the highest *DOM* score is 1.19% higher than the one with the lowest score, holding all other variables at the mean, an 18.74% increase from the unconditional probability of 6.35% for male analysts. In contrast, column (2) shows that the coefficient of *DOM* is negative and significant for female analysts. Economically, the female analyst with the highest *DOM* score is 7.90% less likely to obtain the All-Star status than those with the lowest DOM score, a 74.11% reduction from the unconditional probability of 10.66% for female analysts.[33]

[33] Our results for the control variables are in line with the previous literature: male All-Star probability increases with prior All-Star statues (*LAG_STAR*), brokerage house size (*BROKER_SIZE*), analyst portfolio size

To the extent that the control variables capture an analyst's observable ability and track record, *DOM*'s significant coefficient is more likely to reflect biases rather than capturing analysts' true abilities. The findings suggest that even sophisticated professional financial market players may be susceptible to first impression biases and that such biases have real career influences. Furthermore, the divergent result for female and male analysts suggests that institutional investors' voting decisions may also be affected by traditional gender norms in which dominant males are rewarded, whereas dominant females are penalized. These results are consistent with findings of gender stereotypes in the economics and finance literature discussed earlier.

6. Additional Analyses

We verify the robustness of our findings with respect to three additional issues. First, we compare our sample with the full set of analysts from the I/B/E/S database. Second, we consider the possibility that LinkedIn users retouch their profile pictures. Third, we further control for brokerage and age fixed effects.

6.1 Sample Comparisons

We compare the key characteristics of the analysts with profile pictures available on LinkedIn (Sample 1) with those who maintain profiles but do not provide profile pictures (Sample 2), and with the analysts from the I/B/E/S database (Sample 3). Appendix Table 3 Panels A and B present the average characteristics for the three samples for the period of 2000-2017 (for which LinkedIn started to gain popularity) and 1990-2017, respectively. Panel A shows that, of the 4,343 analysts covered in I/B/E/S, 1149 (or 26%) maintain a profile on LinkedIn, of which 582 (or 51%)

(*PORTFOLIO_SIZE*) and value (*PORFOLIO_CAP*), and decreases with average forecast error (*MEAN_ERROR*). Note that the previous studies do not consider gender (e,g. Emery and Li 2009). Female analyst All-Star probability increases with *LAG_STAR* and *BROKER_SIZE* but decreases with *PORTFOLIO_SIZE*.

include a picture in their profiles. The difference column "(1)-(2)" shows that the analysts with a profile picture share similar characteristics to those without a picture in terms of forecast accuracy, career outcomes, experience, portfolio size and industry coverage, broker affiliation, and the firms they cover. The comparison gives confidence that sample selection is unlikely to be responsible for the trait findings for accuracy.

Compared to the analysts covered in I/B/E/S, Panel A difference column "(1)-(3)" shows that those who joined LinkedIn have similar forecast accuracy, but are more likely to be All-Star analysts and are more experienced, and tend to cover larger firms and growth firms. The comparison suggests that the analysts in our paper make up a substantial portion of the analyst population and tend to be the more important players in the market. Panel B presents the comparison for the period of 1990-2017, for which 17.11% of analysts in I/B/E/S are also in LinkedIn.[34] The pattern of sample differences is similar to those in Panel A.

6.2 Re-touched Photographs

It is possible that LinkedIn users retouch their profile pictures using photo-editing software, in which case the trait measures extracted from them may not capture perceptions of the analysts in real life. We apply a technique developed in Wang et al. (2019) to identify re-touched photos to address this concern.[35] Specifically, we analyze each image with a deep learning model to estimate the probability that the input image has been edited. As shown in Table A5, Panel A, the mean editing probability for pictures in our sample is low, at less than 1%.

[34] Analysts who retire before 2010 are likely to be absent from LinkedIn, resulting in a drop in the percentages of I/B/E/S analysts who are also in LinkedIn

[35] We are grateful to Wang et al. (2019) for sharing their codes, available at https://github.com/PeterWang512/FALdetector.

We identified 12 analysts with an editing probability of greater than or equal to 10%. We then conduct robustness checks by excluding these analysts and replicate the key findings. Table A4 Panel B presents the results on forecast accuracy and analysts' career outcomes, while Panel C presents the result on market reactions to analyst forecasts. The results remain very similar to the main results presented in Tables 2, 7, 8, and 9, suggesting that edited profile pictures do not drive our findings.

6.3 Brokerage Fixed Effects and Age Fixed Effects

It is possible that brokerage houses may prefer to hire analysts with certain facial traits. If so, the observed relation between analysts' facial characteristics and their performance may be driven by associated brokerage characteristics rather than by analyst facial traits. Also, *ATTRACT* is negatively correlated with age, which may be associated with experience and risk-taking. Table A5 presents the robustness checks, in which we introduce brokerage- and age-fixed effects. We include both fixed effects in the analyses, except when the dependent variable is I_{STAR}. The variables I_{STAR} and brokerage house ID are highly correlated, and 74% of broker-year observations have no all-star analyst, so there is little variation in I_{STAR}. Panel A presents the result on forecast accuracy and analysts' career outcome, while Panel B presents the result on market reactions to analyst forecasts. The results remain very similar to the main results presented in Tables 2, 7, 8 and 9.

7. Conclusion Remarks

Evidence from psychology indicates that people form snap impressions about the traits of others from even a fleeting glance at faces, and that these impressions, despite questionable validity, predict many important decisions (Todorov 2017). We employ the machine learning neural network method of Vernon et al. (2014) to extract three trait impression factors—impressions about trustworthiness, dominance, and attractiveness–from US sell-side analyst photos. We test whether these impression factors are associated with measures of analyst behavior, performance, and capital- and labor-market outcomes.

We find that the trustworthiness (*TRUST*) and dominance (*DOM*) factors are positively associated with both the quality and quantity of analysts' information provision. The most trustworthy-looking and most dominant-appearing analysts produce earnings forecasts that are more accurate than those with the lowest scores, and such analysts also tend to generate longer reports. Analysts with the highest *DOM* are much more likely to ask questions in conference calls, and those with the highest *TRUST* score are more likely to herd with managers' guidance forecasts. Furthermore, we find that the return sensitivity to EPS revision is also incrementally higher for revisions issued by high-*TRUST* and high-*DOM* analysts, after controlling for other observable measures of analyst skills.

We interpret the above findings as follows. The *DOM* and *TRUST* traits are associated, at least in part, with greater success by the analysts to acquire private information so as to be able to produce more accurate forecasts. A manager's perception that an analyst is trustworthy encourages the manager to share private information more readily. Analysts who seem aggressive or confident—traits typically associated with dominance—also seem better able to elicit private information from the manager. Confidence or aggressiveness may be associated with a greater willingness to ask questions to get information. Investors also appear to be more willing to respond to information produced by analysts who seem more trustworthy and confident to them. In sum, analysts who appear trustworthy and dominant to managers and capital market participants produce superior outcomes for the analysts.

The results for the attractiveness (*ATTRACT*) factor is more nuanced. We find that *ATTRACT* is positively associated with forecast accuracy for junior analysts and during the pre-Reg FD period, but not for senior analysts and during the post-Reg FD period. We interpret these findings as suggesting that attractiveness provides analysts with an access-to-manager advantage at the beginning of a relatively new relationship with the manager of the firm they are covering. This advantage is removed when other positive qualities of the analysts become apparent to the manager over a longer relationship. Pre-Reg FD Access advantage is important but not post-Reg FD, so the attractiveness trait advantage is present in the former but not the latter.

We also find interesting results pertaining to gender differences. While female analysts tend to produce more accurate forecasts, we find a negative association between *DOM* and forecast accuracy for female analysts. For career outcomes, the *DOM* trait helps male analysts to obtain All-Star status. The apparent "dominance penalty" for female analysts in acquiring information for accuracy and resulting low ranking by peers suggests that there may be some validity to the presence of gender stereotypes that discriminates against women in the corporate world.

Overall, our findings suggest that the facial appearances of analysts are important for their performance and career. The dominant and trustworthy traits improve accuracy and increase the chance of All-Star status. These effects are long-lived and are present even for experienced analysts. The benefits of attractiveness seem more short-lived, sensitive to regulatory disclosure regime, and are diminished by other positive trait qualities that may emerge in longer-term social interactions. Finally, our results also suggest that female analysts face challenges unique to their gender, possibly resulting from societal gender stereotypes about women in a profession that in the past, was primarily dominated by men.

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Table 1: Summary Statistics

This table summarizes the main variables (Panel A) and the pairwise Pearson correlation matrix (Panel B). At the analyst level, *TRUST_Raw*, *ATTRACT_Raw*, and *DOM_Raw* are an analyst's raw trustworthiness, attractiveness, and dominance scores, respectively. *TRUST_Raw_Male, ATTRACT_Raw_Male*, and *DOM_Raw_Male* are the corresponding factor scores for the male analyst sample, and *TRUST_Raw_Female, ATTRACT_Raw_Female*, and *DOM_Raw_Female* are the corresponding factor scores for the female sample. *fWHR* is an analyst's facial width-to-height ratio. The following variables are measured at the analyst-year level: I_{STAR} is an indicator variable taking a value of 1 if an analyst is elected an All-Star Analyst and zero otherwise; I_{JUNIOR} is an indicator variable taking a value of 1 if an analyst is within his or her first two years following an industry and zero otherwise; *PAGES* is the natural logarithm of the total number of pages includes in an analyst's reports about a firm; *CALLS* is the natural logarithm of one plus the total number of conference calls the analyst actively participated in; *MEAN_ERROR* is the average proportional mean absolute error of all forecasts issued by an analyst; *PORTFOLIO_CAP* is the sum of the market capitalization of firms (in logarithms) covered by an analyst. The following set variables are measured at the forecast-level. *ACCURACY* is the negative value of the proportional mean absolute forecast error. I_{HERD} is an indicator set to one if the absolute value of the difference between an analyst forecast and the corresponding management guidance is less than or equal to one cent. *AGE* is an analyst's age; *TOP10* is an indicator variable that takes a value of one if an analyst is affiliated with a top 10 brokerage house and zero otherwise; general experience *(GEXP)* and firm-specific experience *(FEXP)* are the numbers of years since an analyst appeared in I/B/E/S and from the analyst's first forecast of the firm, respectively; *PORTFOLIO_SIZE* and *SIC2* refer to the numbers of firms and 2-digit SIC industries an analyst covers, capturing an analyst's busyness and job complexity, respectively; and *HORIZON* is the number of days between the forecast date and the earnings announcement date. We adjust the above control variables by subtracting the corresponding mean value across all analysts covering the firm over the same quarter and denote the adjusted variables *DAGE*, *DTOP10*, *DGEXP*, *DFEXP*, *DPORTFOLIO_SIZE*, *DSIC2*, and *DHORIZON*. *BROKER_SIZE* is the size of the brokerage house that an analyst is affiliated with, measured by the number of analysts it employs. In terms of firm characteristics, *ANALYST_FOLLOWING* is the number of analysts following a firm, *SIZE* is the natural log of market capitalization, *BM* is the book-to-market ratio of the firm, and RET_{6m} is the prior six-month market-adjusted buy-and-hold returns. *, **, and *** indicates significance at the 10%, 5% and 1% level, respectively.

Panel A: Summary Statistics

Variables	N	Mean	SD	P25	Median	P75	Skewness	Kurtosis
Analyst Level								
TRUST_Raw	795	0.2083	0.3353	-0.0595	0.2556	0.4633	-0.1760	2.3246
ATTRACT_Raw	795	0.0552	0.2574	-0.1041	0.0506	0.2164	0.0043	3.2647
DOM_Raw	795	0.1597	0.2356	0.0268	0.1697	0.3157	-0.3768	3.3269
fWHR	795	2.1549	0.1811	1.7370	2.0310	2.1500	2.2734	2.6013
TRUST_Raw – Male	694	0.1956	0.3294	-0.0620	0.2439	0.4407	-0.1687	2.3934
ATTRAC_Raw – Male	694	0.0332	0.2459	-0.1249	0.0294	0.1840	-0.0450	3.3887
DOM_Raw– Male	694	0.1817	0.2249	0.0560	0.1936	0.3303	-0.4290	3.6370
TRUST_Raw – Female	101	0.2962	0.3634	-0.0331	0.3951	0.5913	-0.3678	2.0395
ATTRACT_Raw– Female	101	0.2084	0.2835	-0.0029	0.2359	0.3901	-0.3157	2.9600
DOM_Raw – Female	101	0.0074	0.2521	-0.1610	-0.0029	0.1577	0.2470	2.9702

Table 1 Panel A (continued)

Variables	N	Mean	SD	P25	Median	P75	Skewness	Kurtosis
Analyst-Year Level								
I_{STAR}	5758	0.0764						
I_{JUNIOR}	6356	0.4520						
PAGES	6325	2.9060	0.7407	2.3979	2.9444	3.4340	0.0511	2.9860
CALLS	5188	2.5908	1.5523	1.3863	3.0910	3.8712	0.5924	1.9529
MEAN_ERROR	5758	0.0057	0.3078	-0.1510	-0.0295	0.1056	2.6180	22.3345
BROKER_SIZE	5758	73.6834	61.4003	2.0000	25.000	57.00	112.00	284.00
PORTFOLIO_CAP	5758	15.4775	1.3256	14.6413	15.5728	16.3880	-0.6319	6.1113
Forecast Level								
ACCURACY	190600	0.0174	0.6743	-0.2444	0.0526	0.4255	-1.2569	5.9656
I_{HERD}	47096	0.5940	0.4911	0.0000	0.0000	1.0000	1.0000	1.0000
DAGE	190600	-0.0938	6.7699	-4.0000	0.0000	3.2500	0.3836	4.0945
DTOP10	190600	0.0013	0.1888	-0.5000	0.0000	0.0000	0.0000	0.8333
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
DPORTFOLIOSIZE	190600	0.0577	8.7285	-4.4000	0.0000	3.6667	1.2491	12.5926
DSIC2	190600	0.0143	1.2244	-0.5000	0.0000	0.5000	0.7154	7.7352
DHORIZON	190600	-0.3755	31.3757	-15.1250	0.0000	10.1000	0.5456	5.8394
ANALYST_FOLLOWING	190600	4.4680	3.1687	2.0000	4.0000	6.0000	1.1404	3.9926
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

Panel B: Pearson Correlations of Analyst-Year Level Variables

	TRUST	*ATTRACT*	*DOM*	I_{HERD}	*PAGES*	*CALLS*
ATTRACT	0.1048*					
DOM	-0.0145	-0.4345*				
I_{HERD}	0.0201	0.0406	-0.0424			
PAGES	-0.0929*	-0.0326	0.0359	0.0664*		
CALLS	0.0345	-0.0070	0.0172	0.0468	0.1328*	
I_{STAR}	0.0476	0.0266	-0.0089	0.0271	0.0205	0.0732*

Table 2: Baseline Regression - Facial Traits and Forecast Accuracy

This table reports panel regression estimates of the effect of analyst facial traits on analyst forecast accuracy. The dependent variable *ACCURACY* is the relative accuracy of an analyst forecast, defined as the negative proportional mean absolute forecast error. *TRUST*, *ATTRACT*, and *DOM* correspond to the gender- and industry-adjusted (2-digit SIC) factors of trustworthiness, attractiveness, and dominance, respectively. We include the following control variables. *fWHR* is *the* analyst's gender- and industry-adjusted facial width-to-height ratio. *ANALYST_FOLLOWING* is the number of analysts following the firm. *DTOP10* is the peer-adjusted probability of Top 10 brokerage affiliations. *DGEXP* is the peer-adjusted general experience of an analyst. *DFEXP* is the peer-adjusted firm-specific experience of an analyst. *DAGE* is the peer-adjusted age of an analyst. *DHORIZON* is the forecast horizon adjusted by all other forecasts. *DSIC2* is the peer-adjusted number of industries followed by an analyst. *DPORTFOLIO_SIZE* is the peer-adjusted number of firms followed by the analyst. *SIZE* is the market capitalization of the firm, BM is the book-to-market ratio, RET_{6M} is the abnormal return in the past six months. I_{FEMALE} is an indicator variable taking 1 one analyst is female, and 0 otherwise. Columns (1) to (3) report the estimation results by including the three facial traits one at a time. Column (5) and (6) include all three orthogonalized facial traits. Columns (4) and (5) includes the standardized raw *fWHR* score, and column (6) includes the ranking of analyst *fWHR* score within the same gender-year-industry. We include a constant and year and industry fixed effects, cluster the standard errors by firm and by analyst, and present the *t*-statistics in parentheses. All coefficients are multiplied by 100. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
TRUST	3.5159***				2.5872***	2.7677***
	(3.60)				(2.83)	(2.99)
ATTRACT		0.2439			0.8710	0.8485
		(0.24)			(0.77)	(0.74)
DOM			3.5265***		5.5608***	5.5518***
			(3.37)		(4.12)	(4.11)
fWHR				0.9482***	0.7087**	1.9512**
				(3.34)	(2.55)	(2.49)
I_{FEMALE}	2.3074***	2.4429***	2.4398***	2.5797***	2.4070***	2.2638***
	(3.47)	(3.64)	(3.65)	(3.83)	(3.58)	(3.41)
ANALYST_FOLLOWING	-0.0288	-0.0292	-0.0355	-0.0310	-0.0361	-0.0377
	(-0.29)	(-0.29)	(-0.35)	(-0.31)	(-0.36)	(-0.37)
DTOP10	-0.4317	-0.3746	-0.3111	-0.3059	-0.4338	-0.4796
	(-0.41)	(-0.36)	(-0.30)	(-0.29)	(-0.41)	(-0.46)
DSIC2	-0.8687***	-0.8723***	-0.8553***	-0.8988***	-0.8691***	-0.8689***
	(-3.91)	(-3.94)	(-3.84)	(-4.07)	(-3.92)	(-3.92)
DGEXP	-0.1241**	-0.1252**	-0.1323**	-0.1224**	-0.1135*	-0.1117*
	(-2.06)	(-2.01)	(-2.17)	(-2.04)	(-1.84)	(-1.82)
DFEXP	0.2769**	0.2830***	0.2884***	0.2820***	0.2795***	0.2763**
	(2.57)	(2.62)	(2.68)	(2.62)	(2.61)	(2.58)
DAGE	-0.0767**	-0.0814**	-0.0941***	-0.0885**	-0.0987***	-0.0978***
	(-2.09)	(-2.24)	(-2.61)	(-2.45)	(-2.73)	(-2.69)
DHORIZON	-0.3023***	-0.3020***	-0.3020***	-0.3015***	-0.3015***	-0.3016***
	(-42.38)	(-42.32)	(-42.36)	(-42.32)	(-42.30)	(-42.30)
DPORTFOLIO_SIZE	0.0772***	0.0745***	0.0796***	0.0810***	0.0831***	0.0820***
	(2.81)	(2.71)	(2.89)	(2.94)	(3.03)	(2.99)
SIZE	0.0680	0.0548	0.0367	0.0747	0.0378	0.0348
	(0.42)	(0.34)	(0.23)	(0.46)	(0.23)	(0.21)
BM	-0.1051	-0.1032	-0.1215	-0.0887	-0.1164	-0.1212
	(-0.77)	(-0.75)	(-0.88)	(-0.65)	(-0.85)	(-0.89)
RET_{6M}	-0.8963	-0.8920	-0.8819	-0.8894	-0.8811	-0.8801
	(-1.54)	(-1.53)	(-1.52)	(-1.53)	(-1.52)	(-1.52)
Adj. R2	0.0230	0.0229	0.0230	0.0230	0.0233	0.0232
N	190600	190600	190600	190600	190600	190600

Table 3: Facial Traits and Forecast Accuracy – The Effect of Earnings Volatility and Market Learning

This table shows how the relation between analyst facial traits and forecast accuracy varies by earnings volatility and analysts' industry experience using panel regressions. The dependent variable *ACCURACY* is the relative accuracy of an analyst forecast, defined as the negative proportional mean absolute forecast error (*PMAFE*). *TRUST*, *ATTRACT*, and *DOM* correspond to the gender- and industry-adjusted trustworthiness, attractiveness, and dominance factors, respectively. In columns (1) through (4), we interact trait factors with an indicator variable (*IND*), I_{HighEV}, that equals to one if earnings volatility is greater than the sample median, and zero otherwise. For columns (5) through (8), *IND* is I_{JUNIOR}, which equals to one if an analyst's industry experience is two years or less and zero otherwise. The list of other control variables is the same as in Table 2. We include a constant and year and industry fixed effects, cluster the standard errors by firm and by analyst, and present the *t*-statistics in parentheses. All coefficients are multiplied by 100. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	Earnings Volatility *IND*= I_{HIGH_EV}				***Industry Experience*** *IND*= I_{JUNIOR}			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*TRUST * IND*	3.0650*			2.8074*	-1.2692			-0.9642
	(1.90)			(1.77)	(-0.74)			(-0.57)
*ATTRACT * IND*		-0.0186		-0.4632		4.2593**		4.2608**
		(-0.01)		(-0.25)		(2.31)		(2.07)
*DOM * IND*			-0.6723	-1.7640			-3.6912**	-3.6436
			(-0.40)	(-0.78)			(-2.06)	(-1.52)
TRUST	1.1764			1.5040	2.7778***			2.9208***
	(1.04)			(1.35)	(2.59)			(2.78)
ATTRACT		0.2637		0.9894		-0.7288		-0.1242
		(0.22)		(0.73)		(-0.62)		(-0.10)
DOM			3.4320***	5.8055***			4.1435***	6.1429***
			(2.76)	(3.59)			(3.52)	(4.03)
IND	-1.5470*	-0.1364	0.1726	-0.3731	-0.7405	-3.4025***	0.5327	-1.2190
	(-1.75)	(-0.16)	(0.18)	(-0.23)	(-0.78)	(-3.35)	(0.55)	(-0.67)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Adj. R2	0.0228	0.0228	0.0229	0.0230	0.0228	0.0227	0.0228	0.0230
N	188678	188678	188678	188678	190600	190600	190600	190600

Table 4: Facial Traits and Forecast Accuracy - The Impact of Reg-FD

This table shows the result on how Regulation FD impacts the effect of analyst facial traits on forecast accuracy, using panel regression analysis. We split the overall sample into pre- (1900-2000) and post-Reg FD (2000-2017) periods. The dependent variable *ACCURACY* is the relative accuracy of an analyst forecast, defined as the negative proportional mean absolute forecast error (*PMAFE*). *TRUST*, *ATTRACT*, and *DOM* correspond to the orthogonalized and gender- and industry-adjusted trustworthiness, attractiveness, and dominance factors, respectively. The list of control variables is the same as in Table 2. We include a constant and year and industry fixed effects, cluster the standard errors by firm and by analyst, and present the *t*-statistics in parentheses. All coefficients are multiplied by 100. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	Pre Reg-FD (1990 - 2000)	**Post-Reg-FD** (2000 - 2017)
TRUST	-1.6771	2.9986***
	(-0.53)	(3.00)
ATTRACT	5.5434*	0.7319
	(1.67)	(0.59)
DOM	3.6570	5.6370***
	(0.90)	(3.87)
IFEMALE	0.1975	2.2196***
	(0.09)	(3.10)
Controls	YES	YES
Adj. R2	0.0509	0.0230
N	17151	172693

Table 5: Facial Traits and Analyst Report Length

This table shows the result of how analyst facial traits affect their report length using analyst-firm-year observations. The dependent variable *PAGES* is the natural logarithm of the total number of pages of reports issued by an analyst for a firm-year. *TRUST*, *ATTRACT*, and *DOM* correspond to the gender- and industry-adjusted trustworthiness, attractiveness, and dominance factors, respectively. Column (1) to (3) include the adjusted facial factors one at a time, and column (4) includes all three orthogonalized facial traits. *fWHR* is the analyst's gender- and industry-adjusted facial width-to-height ratio and I_{FEMALE} is the female gender indicator variable. *AGE* is the age of an analyst. The remaining control variables are measured annually for the preceding year: the number of analysts following the firm (*ANALYST_FOLLOWING*), the market capitalization of the firm (*SIZE*), the book-to-market ratio (*BM*), the abnormal return in the past six months (RET_{6M}), the size of the brokerage house (*BROKER_SIZE*), the number, total market value, and average book-to-market ratios of firms that the analyst covers (*PORTFOLIO_SIZE*, *PORTFOLIO_CAP*, and *MEAN_BM*), the number of industries that the analyst covers (SIC2), the general- and firm-specific experience of the analyst (*GEXP* and *FEXP*), and the analyst's average forecast error (*MEAN ERROR*). We include a constant and firm and year fixed effects, cluster the standard errors by firm and year, and present the *t*-statistics in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
TRUST	0.1545***			0.1633***
	(3.23)			(3.42)
ATTRACT		-0.0274		-0.0112
		(-0.64)		(-0.22)
DOM			0.1066**	0.1618**
			(2.43)	(2.30)
fWHR	-0.0764**	-0.0325	-0.0351	-0.0792**
	(-2.29)	(-1.03)	(-1.11)	(-2.37)
I_{FEMALE}	-0.0327	-0.0236	-0.0274	-0.0367
	(-1.08)	(-0.78)	(-0.91)	(-1.20)
Controls	YES	YES	YES	YES
Adj. R2	0.2086	0.2072	0.2080	0.2096
N	6325	6325	6325	6325

Table 6: Facial Traits, Conference Call Participation, and Herding

This table reports the regression estimates of analyst facial traits on conference call participation and analysts' probability of herding with the management. In Columns (1) and (4), we estimate panel regressions with analyst-year observations. The dependent variable is *CALLS,* the natural logarithm of 1 plus the number of conference calls in which analyst *i* asked at least one question in year *t*. In column (5) to (8), we estimate logistic regression at the forecast level, in which the dependent variable (I_{HERD}) is an indicator variable that takes the value of 1 if the analyst herd with the manager and 0 otherwise. *TRUST*, *ATTRACT*, and *DOM* correspond to the gender- and industry-adjusted trustworthiness, attractiveness, and dominance factors, respectively. Column (1) to (3) and column (5) to (7) include the adjusted facial factors one at a time, and column (4) and column (8) includes all three orthogonalized facial traits. *fWHR* is the analyst's gender- and industry-adjusted facial width-to-height ratio. *AGE* and I_{FEMALE} are analyst age and female gender indicator, respectively. Columns (1)-(4) includes all the control variables included in Table 5 and *FORECAST_FREQ*, the number of EPS forecasts an analyst issues for the firm in the preceding year. The controls for columns (5)-(8) are the same as in Table 2, measured annually for the preceding year. We include year-fixed effects for Column (1) to (4) and industry and year fixed effects for column (5) to (8). We cluster the standard errors by analyst for Column (1) to (4) and by firm and by analyst for column (5) to (8), and present the *t*-statistics for column (1) to (4) and *z*-statistics for column (5) to (8) in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	Conference Call Participation				**Herding with Manager**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TRUST	0.0482			0.0283	0.1558**			0.1425*
	(0.29)			(0.17)	(1.96)			(1.80)
ATTRACT		-0.0188		0.1346		0.1022		0.0748
		(-0.12)		(0.77)		(1.33)		(0.86)
DOM			0.3795**	0.4287**			-0.1481*	-0.1678
			(2.22)	(2.34)			(-1.85)	(-1.51)
fWHR	0.0427	0.0558	0.0498	0.0448	0.0632	0.1046*	0.1059*	0.0654
	(0.33)	(0.45)	(0.40)	(0.35)	(0.99)	(1.75)	(1.78)	(1.03)
I_{FEMALE}	0.0023	0.0023	0.0071	0.0085	0.1242**	0.1304**	0.1369**	0.1258**
	(0.02)	(0.02)	(0.05)	(0.06)	(2.05)	(2.15)	(2.26)	(2.08)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Adj./Pseudo R2	0.4570	0.4569	0.4604	0.4608	0.0675	0.0674	0.0675	0.0676
N	5188	5188	5188	5188	47096	47096	47096	47096

Table 7: Facial Traits and Analyst Activities — Female Subsample

This table shows analyst facial traits on measures analyst information quality and activities for the female analyst sample. The dependent variables in columns (1) through (4) are: forecast accuracy (*ACCURACY*, forecast level), the logarithm of the number of conference calls the analyst participated (*CALLS*, at analyst-year level), the logarithm of the total number of pages in an analysts' reports for a firm (*PAGES*, at analyst-firm-year level), the analyst's tendency to herd with management (I_{HERD}, at forecast level). The facial traits (*TRUST*, *ATTRACT*, and *DOM*) are the orthogonalized and industry-year adjusted perceived trustworthiness, attractiveness, and dominance. *fWHR* is *the* analyst's industry-adjusted facial width-to-height ratio. The other control variables, fixed effects and standard error specifications for columns (1) through (4) correspond to those used in Tables 2, 5, and 6, respectively. We estimate panel regressions for columns (1) through (3) and present *t*-statistics in parentheses. For columns (4), we estimate Logit regressions and present *z*-statistics in parentheses. *t-statistics (z-statistics)* are presented in parentheses. Coefficients in column (1) are multiplied by 100. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	ACCURACY	***CALLS***	***PAGES***	***HERD***
	(1)	(2)	(3)	(4)
TRUST	3.3273	0.1716	0.0478	-0.0635
	(1.20)	(0.51)	(0.28)	(-0.30)
ATTRACT	-5.2610*	0.2520	-0.2703	-0.0353
	(-1.68)	(0.54)	(-1.36)	(-0.12)
DOM	-13.0181***	1.3962**	0.0734	-0.2025
	(-2.76)	(2.12)	(0.25)	(-0.46)
fWHR	-1.3424	0.2554	-0.1557	-0.1579
	(-0.68)	(1.02)	(-1.08)	(-0.96)
Controls	YES	YES	YES	YES
Adj./Pseudo R2	0.0436	0.5258	0.4937	0.0950
N	22196	621	854	6119

Table 8: Facial Traits and Market Reactions to Analyst Forecasts

This table shows panel regression results on the relation between analyst facial traits and market reactions to analyst earnings forecast revisions. The dependent variable is the two-day cumulative abnormal return, *CAR (0,1),* calculated as the difference between the individual stock return CRSP value-weighted index return. *TRUST*, *ATTRACT*, and *DOM* correspond to the orthogonalized and gender- and industry-adjusted trustworthiness, attractiveness, and dominance factors, respectively. Column (2) to (4) include all three adjusted facial factors orthogonalized. *fWHR* is the analyst's gender- and industry-adjusted facial width-to-height ratio. *LAG_ACCURACY* is the negative mean *PMAFE* of the analyst for a firm over the last eight quarters. *REVISION* is the difference between an analyst forecast with consensus forecasts. *ANALYST_FOLLOWING* is the number of analysts following the firm. *ROA* is the return-on-asset. *LEVERAGE* is the debt-to-equity ratio. *SIZE* is the logarithm market capitalization of the company. *BM* is the book-to-market ratio of the company. *BHAR* is the buy-and-hold abnormal return over the past seven days. *HORIZON* is the forecast horizon. I_{FEMALE} is an indicator variable equal to one for females and 0 otherwise. All estimations include a constant term and year and firm fixed effects, with standard errors clustered by firm and by analyst. *t-statistics* are presented in parentheses. All coefficients are multiplied by 100. ***, **, * denotes for significance at the 1%, 5% and 10% level, respectively.

	(1) Full	(2) Full	(3) Male	(4) Female
REVISION	0.6785***	-0.4340	0.0727	0.1074
	(5.51)	(-0.84)	(0.13)	(0.05)
*REVISION * TRUST*		1.0805**	0.9595**	-0.6927
		(2.53)	(2.08)	(-0.41)
*REVISION * ATTRACT*		-0.2766	-0.4400	-0.7876
		(-0.61)	(-0.93)	(-0.44)
*REVISION * DOM*		1.7744***	1.0773	3.2252
		(2.77)	(1.54)	(1.62)
*REVISION * LAG_ACCURACY*		1.8919*	0.9921	9.4820**
		(1.85)	(0.93)	(2.29)
*REVISION * fWHR*		-0.0952	-0.5473	4.3730***
		(-0.21)	(-1.15)	(2.70)
TRUST		-0.1213	-0.1245	0.0604
		(-1.17)	(-1.11)	(0.11)
ATTRACT		-0.1397	-0.1272	-0.0565
		(-1.25)	(-1.05)	(-0.08)
DOM		0.2289	0.2335	-0.2983
		(1.40)	(1.34)	(-0.26)
LAG_ACCURACY	-0.1722	-0.1580	-0.2879	0.6157
	(-0.83)	(-0.76)	(-1.31)	(0.73)
fWHR	-0.0956	-0.0704	-0.0481	-0.2708
	(-1.02)	(-0.70)	(-0.43)	(-0.74)
I_{FEMALE}	0.0972	0.1586*		
	(1.10)	(1.71)		
Other Controls	YES	YES	YES	YES
Adj. R2	0.1700	0.1701	0.1823	0.3070
N	37287	37287	32832	4455

Table 9: Facial Traits and All-Star Analyst Selection Outcomes

This table reports the Logit regression estimates of analyst facial traits on the probability of being selected as an All-Star Analyst. Columns (1) and (2) correspond to the male, and columns (3) and (4) correspond to the female analyst sample. The dependent variable I_{STAR} is the All-Star status indicator variable. *TRUST*, *ATTRACT*, and *DOM* correspond to the orthogonalized and gender- and industry-adjusted factors of trustworthiness, attractiveness, and dominance, respectively. *fWHR* is the analyst's gender- and industry-adjusted facial width-to-height ratio. *AGE* is the age of the analyst. The following variables are measured in the prior year. *LAG_STAR* is the analyst's prior year all-star status; *PORTFOLIO SIZE, PORTFOLIO_CAP*, *MEAN_BM,* and *SIC2* are the numbers, total market capitalization, and average book-to-market value of firms and two-digit *SICs* followed by the analyst, respectively. *BROKER_SIZE* the size of the brokerage house that the analyst is affiliated with. *MEAN_ERROR* is the analyst's mean forecast error for the year. All estimations include an intercept and controlled year fixed effects; *t*-statistics presented in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	Male	**Female**
	(1)	(2)
TRUST	0.3740	-0.4388
	(1.29)	(-0.80)
ATTRACT	0.1990	1.9867
	(0.69)	(1.63)
DOM	1.0943***	-4.4842***
	(2.65)	(-2.68)
fWHR	-0.1183	-0.2221
	(-0.49)	(-0.49)
LAG_STAR	3.7614***	4.2549***
	(18.56)	(7.96)
PORTFOLIO_SIZE	0.0188***	-0.0462*
	(2.72)	(-1.95)
SIC2	0.0257	0.1833
	(0.59)	(1.40)
BROKER_SIZE	0.0464***	0.0302**
	(5.90)	(1.98)
MEAN_ERROR	-1.1172***	-0.7003
	(-3.11)	(-1.10)
PORTFOLIO_CAP	0.0239***	0.0237
	(2.80)	(1.20)
AGE	-0.0186**	0.0879***
	(-2.12)	(3.32)
Pseudo R2	0.5015	0.4727
N	5030	687

Appendix Table A1: Variable Definition

Variable	Definition
PMAFE	The proportional mean absolute forecast error, calculated as an analyst's absolute forecast error (*AFE*) for a firm *j* minus the same-quarter mean absolute forecast error (*MAFE*) for the firm across all analysts, divided by *MAFE*.
ACCURACY	The negative *PMAFE*.
TRUST	An analyst's trustworthiness score, ranked annually among analysts covering the same industry-year and normalized to [0,1].
ATTRACT	An analyst's attractiveness score, ranked annually among analysts covering the same industry-year and normalized to [0,1].
DOM	An analyst's dominance score, ranked annually among analysts covering the same industry-year and normalized to [0,1].
fWHR	An analyst's facial width-to-height ratio, measured as the distance between the left and right zygion (bizygomatic width) relative to the distance between the upper lip and the highest point of the eyelids (upper facial height).
I_{FEMALE}	Indicator variable that equals to one if an analyst is female, and zero otherwise.
I_{HIGHEV}	Indicator variable that equals to one if earnings volatility is greater than the sample median, and zero otherwise.
I_{JUNIOR}	Indicator variable that equals to one if an analyst is in the analyst's first two years following an industry.
I_{HERD}	Indicator variable that equals to one if the absolute value of the difference between analyst ESP forecasts and the proceeding management guidance number is 1 cent or less and zero otherwise.
ANALYST_FOLLOWING	The number of analysts following a firm.
DTOP10	Indicator variable that equals to one if the brokerage house belongs to the top decile size group, minus the corresponding firm-quarter mean across brokerage houses.
DSIC2	The number of two-digit SICs an analyst follows, minus the corresponding firm-quarter mean across analysts.
DGEXP	Number of years an analyst existed in I/B/E/S, minus the corresponding firm-quarter mean across analysts.
DFEXP	The number of years an analyst has covered a firm, minus the corresponding firm-quarter mean across analysts.
DHORIZON	The number of days between the forecast date and the earnings announcement date, minus the corresponding firm-quarter mean across analysts.
DAGE	The age of an analyst, minus the corresponding industry-quarter mean across analysts.
DPORTFOILIO_SIZE	The number of firms in an analyst's portfolio minus the corresponding firm-quarter mean across analysts.
SIZE	The natural log of market capitalization (in $ millions) of the firm that an analyst covers, evaluated at the end of the month prior to the earnings forecast.
BM	Book-to-market ratio of a firm, defined as book value of equity in the fiscal year prior to t divided by the current market value of equity.
ROA	Return-on-asset ratio of a firm, calculated as the income before interest and tax (EBIT) divided by lagged total asset.
LEVERAGE	Debt-to-equity ratio of a firm, calculated as the total equity divided by total asset.
RET_{6M}	Prior six-month cumulative stock return of a firm, adjusted by the CRSP value-weighted index.

Appendix Table A1: Variable Definition (continued)

REVISION	The difference between an analyst's EPS forecast and the consensus forecasts.
HORIZON	The number of days between the forecast date and the earnings announcement date.
CALLS	The natural logarithm of one plus number of conference calls an analyst actively participated during a year.
PAGES	The natural logarithm of the number of pages of reports issued by an analyst for a firm-year.
I_{STAR}	Indicator variable that equals to one if the analyst is named *Institutional Investor*'s All-Star team and zero otherwise.
LAG_STAR	Indicator variable that equals to one if the analyst was named *Institutional Investor*'s All-Star team for at least once in the previous three years, and zero otherwise.
MEAN_ERROR	An analyst's annual average *PMAFE* across all firms covered.
PORTFOLIO SIZE	The number of firms an analyst covers.
PORTFOLIO_CAP	The total market values of the firms an analyst covers.
BROKER_SIZE	The number of analysts a brokerage house employs.
FORECAST_FREQ	The number of EPS forecasts analyst issues for a firm-year.

Table A2: Additional Summary Statistics

This table provides additional summary statistics. Panel A reports the distributional statistics of forecast-level variables by gender and tests the differences in mean with grouped t-tests. Panel B reports correlation coefficients. Variable definitions are the same as in Table 2. ***, **, * denotes significance at the 1%, 5%, and 10% level, respectively.

Panel A. Summary Statistics by Gender

Variables	Male	SE	Female	SE	Diff. (Male-Female)
ACCURACY	0.0140	0.0016	0.0434	0.0044	-0.0294***
TRUST	0.5045	0.0007	0.6291	0.0021	-0.1246***
ATTRACT	0.5014	0.0007	0.7035	0.0019	-0.2021***
DOM	0.5630	0.0007	0.3815	0.0020	0.1815***
ANALYST_FOLLOWING	4.4244	0.0077	4.7984	0.0220	-0.3740***
DTOP10	0.0030	0.0005	-0.0111	0.0012	0.0140***
DGEXP	-0.0038	0.0106	0.0207	0.0278	-0.0245
DFEXP	-0.0275	0.0063	-0.1020	0.0170	0.0745***
DHORIZON	-0.3546	0.0764	-0.5343	0.2122	0.1798
DAGE	-0.1118	0.0166	0.0426	0.0442	-0.1544***
DSIC2	0.0209	0.0030	-0.0357	0.0085	0.0566***
DPORTFOLIO_SIZE	0.2285	0.0217	-1.2389	0.0475	1.4675***
SIZE	14.7864	0.0041	14.7802	0.0110	0.0062
BM	0.5396	0.0025	0.4981	0.0054	0.0414***
RET_{6M}	-0.0109	0.0007	-0.0214	0.0020	0.0104***
N	168404		22196		

Panel B: Correlations

This table provides the pairwise Pearson correlation matrix of variables at the forecast level. The facial traits (*TRUST*, *ATTRACT*, and *DOM*) are perceived trustworthiness, attractiveness and dominance, respectively. Variable list and definitions are the same as in Table 2. * indicates significance at the 5% level.

	PMAFE	*TRUST*	*ATTRACT*	*DOM*	I_{FEMALE}	*BROKER_ SIZE*	*ANALYST_ FOLLOWING*	*DSIC2*
TRUST	-0.0099*							
ATTRACT	-0.0037	0.0898*						
DOM	-0.0062*	-0.0461*	-0.4958*					
I_{FEMALE}	-0.0140*	0.1374*	0.2209*	-0.1991*				
BROKER_SIZE	0.0076*	-0.0067*	0.0868*	0.0090*	0.0127*			
ANALYST_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*

Table A3: Sample Comparisons

This table provides the grouped *t*-test result for analyst level characteristics between analyst with and without profile images. ***, **, * denotes for significance at the 1%, 5% and 10% level, respectively.

Panel A: 2000-2017

	LinkedIn		**I/B/E/S**	**Diff.**	
Variables	(1) Photo	(2) No Photo	(3)	(1)-(2)	(1)-(3)
ACCURACY	-0.0386	-0.0367	-0.031	-0.0019	-0.0077
I_{STAR}	0.0286	0.0293	0.0076	-0.0008	0.0210***
GEXP	7.9585	8.357	7.2979	-0.3985	0.6607**
FEXP	2.9146	3.1019	2.7685	-0.1872	0.1461
SIC2	3.0353	2.9178	2.9585	0.1175	0.0769
PROTFOLIO_SIZE	15.1673	15.129	14.8746	0.0383	0.2926
BROKER_SIZE	69.3311	68.9714	69.1679	0.3598	0.1632
SIZE	15.0125	15.1219	14.7661	-0.1094*	0.2464***
BM	0.5343	0.5636	0.6694	-0.0293	-0.1351***
N	582	557	4343		

Panel B: 1990-2017

	LinkedIn		**I/B/E/S**	**Diff.**	
Variables	(1) Photo	(2) No Photo	(3)	(1)-(2)	(1)-(3)
ACCURACY	-0.0275	-0.0306	-0.0421	0.0031	0.0146*
I_{STAR}	0.0449	0.0425	0.0086	0.0024	0.0363***
GEXP	5.8687	6.072	5.2591	-0.2033	0.6095***
FEXP	2.184	2.2956	2.0356	-0.1116	0.1485**
SIC2	2.8387	2.7295	2.7333	0.1092	0.1054
PROTFOLIO_SIZE	14.7849	14.4938	14.2977	0.2911	0.4872**
BROKER_SIZE	69.3155	69.5739	69.59	-0.2584	-0.2745
SIZE	14.7696	14.8707	14.4802	-0.1011*	0.2894***
BM	0.591	0.5556	0.6393	0.0354	-0.0483
N	783	760	7872		

Table A4: Facial Traits and Forecast Accuracy – Robustness to Photo-Editing

This table presents results of robustness checks considering the probability that LinkedIn profile pictures may be photo edited. Panel A describes the summary statistics of photo-editing probability and Panel B and Panel C presents key results excluding analyst observations with an editing probability of 10% or higher. Panle B columns (1) and (2) correspond to the dependent variable *ACCURACY*, for the full sample and the female subsample, respectively. Columns (3) and (4) correspond to the dependent variable I_{STAR}, for the male and the female subsamples, respectively. The dependent variable in Panel C is *CAR(0,1)*. *TRUST*, *ATTRACT*, and *DOM* correspond to the gender- and industry-adjusted (2-digit SIC) factors of trustworthiness, attractiveness, and dominance, respectively. All control variables, fixed effects, and error-clustering methods are the same as in Tables 2, 8, and 9, respectively. Coefficients in Panel B, columns (1) and (2), and Panel C are multiplied by 100. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Probability of Photo Editing

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: Facial Traits and Outcome Variables

	(1) *ACCURACY* (Full)	(2) *ACCURACY* (Female)	(3) I_{STAR} (Male)	(4) I_{STAR} (Female)
TRUST	1.4986**	1.6982	0.3959	-0.8133
	(1.99)	(0.63)	(1.35)	(-1.41)
ATTRACT	-0.5281	-4.5467	0.2109	1.8758
	(-0.56)	(-1.50)	(0.72)	(1.49)
DOM	4.5893***	-13.7653***	1.0910***	-4.7185***
	(3.70)	(-3.01)	(2.63)	(-2.68)
I_{FEMALE}	2.4556***			
	(3.65)			
Controls	YES	YES	YES	YES
Adj. R2	0.0226	0.0438	0.5034	0.4911
N	188084	22119	4953	672

Panel C: Facial Traits and Market Reaction to Earning Forecast Revisions

	(1) Full	(2) Full	(3) Male	(4) Female
REVISION	0.6510***	-0.5876	-0.0954	0.0892
	(5.27)	(-1.13)	(-0.17)	(0.04)
*REVISION * TRUST*		1.0555**	0.9166**	-0.7179
		(2.47)	(1.98)	(-0.42)
*REVISION * ATTRACT*		-0.1499	-0.3050	-0.7515
		(-0.33)	(-0.64)	(-0.43)
*REVISION * DOM*		1.8113***	1.1229	3.2597
		(2.82)	(1.60)	(1.62)
*REVISION * LAG_ACCURACY*		1.8932*	0.8961	9.4255**
		(1.84)	(0.83)	(2.24)
Controls	YES	YES	YES	YES
Adj. R2	0.1723	0.1730	0.1840	0.3093
N	36718	36718	32319	4399

Table A5: Robustness Checks, with Brokerage and Analyst Age Fixed Effects

This table reports results of robustness checks controlling for brokerage house and analyst age fixed effects. Panel A columns (1) and (2) correspond to the dependent variable *ACCURACY*, for the full sample and the female subsample, respectively. Columns (3) and (4) correspond to the dependent variable I_{STAR}, for the male and the female subsamples, respectively. The dependent variable in Panel B is *CAR(0,1)*. *TRUST*, *ATTRACT*, and *DOM* correspond to the gender- and industry-adjusted (2-digit SIC) factors of trustworthiness, attractiveness, and dominance, respectively. All control variables, baseline fixed effects, and error-clustering method are the same as in Tables 2, 8, and 9, respectively. Coefficients in Panel A, columns (1) and (2), and Panel B are multiplied by 100. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Facial Traits and Outcome Variables

	(1) *ACCURACY* (Full)	(2) *ACCURACY* (Female)	(3) I_{STAR} (Male)	(4) I_{STAR} (Female)
TRUST	2.8751***	5.5623	0.3959	-0.8133
	(3.41)	(0.94)	(1.35)	(-1.41)
ATTRACT	-1.1995	-10.7958*	0.2109	1.8758
	(-1.11)	(-1.85)	(0.72)	(1.49)
DOM	4.8878***	-24.2076***	1.0910***	-4.7185***
	(3.51)		(2.63)	(-2.68)
I_{FEMALE}	1.8399**			
	(2.37)			
Controls	YES	YES	YES	YES
Brokerage FE	YES	YES		
Age FE	YES	YES	YES	YES
Adj. R2	0.0320	0.0540	0.5116	0.5118
N	190600	22196	4984	674

Panel B: Facial Traits and Market Reactions to Analyst Forecasts

	(1) Full	(2) Full	(3) Male	(4) Female
REVISION	0.6976***	-0.4620	0.0266	0.3341
	(5.65)	(-0.89)	(0.05)	(0.15)
*REVISION * TRUST*		1.0863**	0.9251**	-0.6201
		(2.53)	(1.99)	(-0.36)
*REVISION * ATTRACT*		-0.2381	-0.3767	-1.0003
		(-0.53)	(-0.79)	(-0.56)
*REVISION * DOM*		1.7164***	1.0620	3.5097*
		(2.67)	(1.51)	(1.75)
*REVISION * LAG_ACCURACY*		1.4418	0.5469	9.2887**
		(1.40)	(0.51)	(2.22)
Controls	YES	YES	YES	YES
Brokerage FE	YES	YES	YES	YES
Age FE	YES	YES	YES	YES
Adj. R2	0.1780	0.1781	0.1914	0.3336
N	37287	37287	32832	4455

Appendix B: Extraction and Validation of Face-Based Trait Factors

In this appendix, we describe the procedures used to extract trait factor scores using analysts' profile photos as inputs. We first use an automated facial point annotation tool to delineate 68 important fiducial landmark-points of a face. The process is illustrated in Appendix Figure B1.[36] We then combine the coordinates of these 68 fiducial landmark-points with the brightness and HSV (Hue, Saturation, and Value) properties of pixels for the corresponding facial area to calculate the 65 physical attributes for the face, listed in Appendix Table B1.

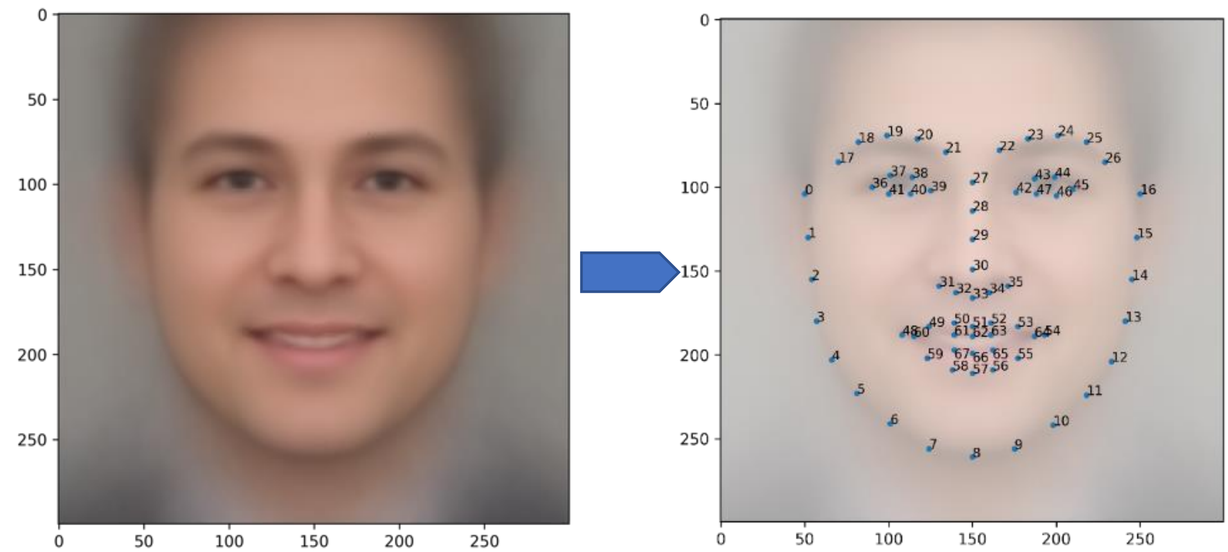
We apply the Vernon et al. (2014) machine learning model to the 65 attributes and obtain the three trait factors' raw values, *TRUST_Raw, ATRACT_Raw, DOM_Raw*. Next, we validate the ML-generated trait factor scores with traits rated by human subjects whom we hired on Amazon Mechanical Turk. We ask ten raters (five male, five female) to rank a randomly selected subsample of 100 analyst photos along the three trait dimensions. The Pearson correlations between the model-predicted traits and human-rated traits are 0.92, 0.75, and 0.72 for trustworthiness, attractiveness, and dominance, respectively; all are significant at the 0.01 level. These correlations are similar to those obtained in Vernon et al. (2014), confirming that the model performed reasonably well in our sample.

Appendix Figure B2 provides an illustration of synthesized faces with varying trait scores. Each row corresponds to faces when we vary one trait factor from the lowest decile value to the highest, using the average face in our sample as the benchmark. Images at the left end of each row correspond to the low values of the trait factors, and images at the right end correspond to the high values.

[36] The tool is developed by the Intelligent Behavior Understanding Group (i-bug) at the Imperial College (https://ibug.doc.ic.ac.uk /resources/facial-point-annotations/). This method has been widely used in facial recognition tasks such as mobile payment and security systems (Sagonas et al., 2016).

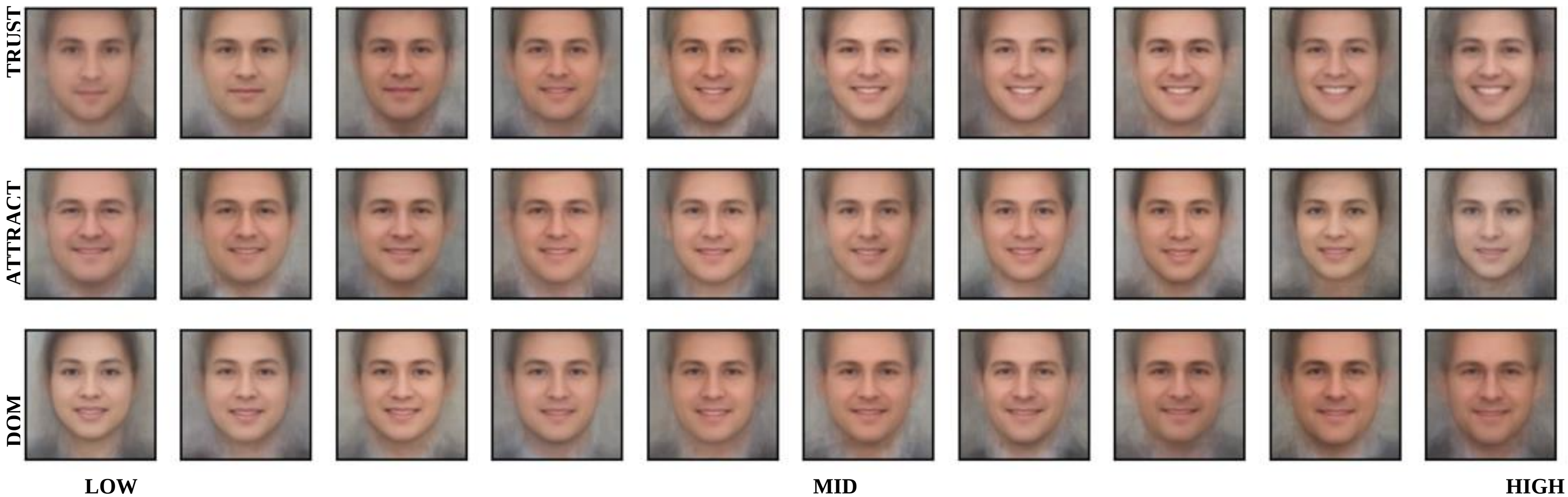
Appendix Figure B1: Illustration of Delineating Process

We illustrate the procedures used to delineate 68 important fiducial landmark-points of a face.



Appendix Figure B2: Average Faces of Varying Trait Factor Values

This figure provides a illustration of synthesized faces with varying trait scores. Each row corresponds to faces when we vary one trait factor from the lowest decile value to the highest, using the average face in our sample as the benchmark. Images at the left end of each row correspond to the low values of the trait factors and images at the right end correspond to the high values.



Appendix Table B1: List of 65 Facial Attributes and Calculation Descriptions

The following table illustrates the 65 facial attributes and how they are calculating from the 68 fiducial landmarks following Vernon (2014).

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 0:16, 17:26
50.	Skin value	
51.	Eyebrow hue	
52.	Eyebrow saturation	Color information (HSV format) for area enclosed by points 17:21,22:26
53.	Eyebrow value	
54.	Lip hue	
55.	Lip saturation	Color information (HSV format) for area enclosed by points 48:59
56.	Lip value	
57.	Iris hue	
58.	Iris saturation	Color information (HSV format) for area enclosed by 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)