Journal of Accounting Research

DOI: 10.1111/1475-679X.12428
Journal of Accounting Research
Vol. No. March 2022
Printed in U.S.A.

CHICAGO BOOTH

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

LIN PENG,* SIEW HONG TEOH,† YAKUN WANG,‡ AND JIAWEN YAN§

Received 1 December 2020; accepted 2 February 2022

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*Zicklin School of Business, Baruch College, City University of New York, and Faculty of Economics and Darwin College, University of Cambridge; †Anderson School of Management, University of California, Los Angeles; ‡School of Management and Economics, The Chinese University of Hong Kong, Shenzhen, and Shenzhen Finance Institute; §SC Johnson College of Business, Cornell University

Accepted by Douglas Skinner. The paper was previously circulated under the title "Face Value: Trait Inference, Performance Characteristics, and Market Outcomes for Financial Analysts." We thank an anonymous reviewer, Gauri Bhat, Elizabeth Blankespoor, Donal Byard, Ed deHaan, Hemang Desai, Phil Dybvig, Rich Frankel, Luzi Hail, Chad Ham, Doug Hanna, David Hirshleifer, Mingyi Hung, Narasimhan Jegadeesh, Da Ke (discussant), Lisa Koonce, Mark Lang, Christian Leuz, Edward X. Li, Ningzhong Li, Xinlei Li, Chuchu Liang, Brandon Lock, Ben Lourie, Mark Maffett, Xiumin Martin, Arthur Morris, Jing Pan, Devin Shanthikumar, Terry Shevlin, Derrell Stice, Alex Todorov, Sorabh Tomar, Marcel Tuijn, Sean Wang, George Yang, Hayoung Yoon, Huai Zhang, Bohui Zhang, Dexin Zhou, Chenqi Zhu, and conference and seminar participants at the Chicago Quantitative Alliance Annual Conference, Baruch College, Hong Kong University, Hong Kong University of Science and Technology, Tsinghua University, The Chinese University of Hong Kong, Shenzhen, Southern Methodist University, the University of California Irvine, the University of Oregon, Washington University in St. Louis, the University of Zurich, the CICF Conference, and the Midwest Finance Association Conference for helpful feedback and suggestions. We further thank participants from the *Journal of Accounting Research* conference for many helpful comments. Lin Peng acknowledges the Krell research grant and the Keynes Fund for financial support. An online appendix to this paper can be downloaded at http://research.chicagobooth.edu/arc/journal-of-accounting-research/online-supplements.

ABSTRACT

Using machine learning–based algorithms, we measure key impressions about sell-side analysts using their LinkedIn photos. We find that impressions of analysts' trustworthiness (*TRUST*) and dominance (*DOM*) are positively associated with forecast accuracy, especially after recent in-person meetings between analysts and firm managers. High *TRUST* also enhances stock return sensitivity to forecast revisions, especially for stocks with high institutional ownership. In contrast, the impression of analysts' attractiveness (*ATTRACT*) is only positively associated with accuracy for new analysts or when a firm has a new CEO or CFO. Furthermore, while high *DOM* helps male analysts' chances of attaining All-Star status, it reduces female analysts' accuracy and the likelihood of winning the All-Star award. In addition, the relation between *TRUST* and accuracy is modulated by the disclosure environment and is attenuated by Regulation Fair Disclosure. Our results suggest that face impressions influence analysts' access to information and the perceived credibility of their reports.

JEL codes: D83, G14, G24, G28, G41, J16, M41, M48

Keywords: machine learning; facial recognition; trait impressions; analysts; gender discrimination; EPS forecasts; All-Star Analysts; forecast revision; social interactions

1. *Introduction*

Humans form first impressions about other people from their faces spontaneously within milliseconds.[1] We refer to these judgments as face impressions. Face impressions have powerful effects on visual attention, trait inferences, social judgments, and social interactions (Hugenberg and Wilson [2013], Todorov [2017]). For example, people judged as more attractive or trustworthy have more positive legal, political, and labor market outcomes.[2] There is also growing evidence that face impressions have capital market consequences.[3]

The evidence that face impressions have consequential outcomes motivates our study of face impressions of sell-side analysts. Information

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[1] See, for example, Asch [1946], Hassin and Trope [2000], Willis and Todorov [2006], Bar, Neta, and Linz [2006], and Todorov [2017].

[2] Attractive people win more legal cases (Zebrowitz and McDonald [1991]), earn a beauty premium (Mobius and Rosenblat [2006]), have higher teaching ratings (Hamermesh and Parker [2005]), and are more successful in online dating (Finkel et al. [2012]). Trustworthy-looking people are more likely to win elections (Todorov et al. [2005]) and move up the corporate ladder (Linke, Saribay, and Kleisner [2016]).

[3] Examples include studies of borrower trustworthiness on loan terms (Duarte, Siegel, and Young [2012]), CEO competence on compensation (Graham, Harvey, and Puri [2017]), analyst beauty on forecast accuracy (Cao et al. [2020], Li et al. [2020]), and auditor trustworthiness on auditor tenure and audit fees (Hsieh et al. [2020]). Another set of studies extracts trait impressions from body language using videos to examine entrepreneurial funding (Blankespoor, Hendricks, and Miller [2017], Huang et al. [2020]; Hu and Ma [2020]).

possessors (firm insiders, industry experts, analyst peers) and clients (investors, buy-side analysts) form perceptions about analysts via social interactions. We study whether and how perceptions about analysts are associated with analyst outcomes to obtain insights into the role of impressions in information acquisition and information dissemination in capital markets.

Most face impression studies use human ratings of faces to measure one or a few specific personality traits selected by the researchers, such as beauty and competence. However, people form a multitude of impressions from observing faces. We apply recent social psychology models and artificial intelligence (AI) machine learning (ML) techniques to extract a set of key factors that comprehensively measure a multitude of impressions gained from observing faces.

We first use facial recognition software to identify a large set of facial features from the LinkedIn profile photographs of U.S. sell-side analysts. We then apply the ML algorithms to obtain empirical measures for three key face impressions or *Face Factors*: trustworthiness (*TRUST*), attractiveness (*ATTRACT*), and dominance (*DOM*). We examine the associations of these factors with analyst forecast accuracy, stock return sensitivity to analyst forecast revisions, and analyst attainment of All-Star status. We further explore face factor effects across different situational contexts to provide additional insights about the potential channels for impression effects.

Cognitive psychology suggests that the wide range of personality traits in face impressions can be reduced to these three key dimensions, which together capture a substantial amount (72%) of the variation in face impressions (Oosterhof and Todorov [2008], Sutherland et al. [2013]). The *TRUST* factor reflects multiple traits related to the observer's perceptions about the observed's intention to help or hurt the observer. The *DOM* factor concerns perceptions about the ability of the observed to carry out intentions. Oosterhof and Todorov [2008] suggest that humans have developed these perceptions through natural selection over our evolutionary history as shortcuts in cognitive processing to appraise threats in our social environment to aid survival. Regarding *ATTRACT*, Sutherland et al. [2013] suggest that the factor is associated with unconscious fitness and mate selection cues.[4]

Perceptions about the personality traits formed from interactions with the financial analysts affect the analysts' information access. We hypothesize that information possessors may be more willing to share information with analysts they trust more (high-*TRUST* analysts), who they perceive as more effective and efficient in processing and disseminating information (high-*DOM* analysts), or who they find more attractive or novel (high-*ATTRACT*

[4] The *TRUST* factor loads highest on traits such as approachability, trustworthiness, and degree of smile, the *DOM* factor loads highest on dominance, sexual dimorphism, and confidence (Vernon et al. [2014]), and the *ATTRACT* factor loads highest on attractiveness and health (Sutherland et al. [2013]).

analysts).[5] The potential greater access to information for the analysts with higher scores on these three factors, therefore, may help improve their accuracy.

The impression effects may be transient if incorrect perceptions get corrected over time, or they may be long-lasting if self-fulfilling prophecy effects reinforce initial impressions. The higher accuracy from improved access to information for the high-*TRUST* or high-*DOM* analysts may reinforce the information sharers' initial perceptions about the analyst to encourage continued sharing of information to create these self-fulling prophecy feedback effects. In contrast, the *ATTRACT* factor is less likely to generate a persistent self-fulfilling positive feedback effect. The initial novelty of an attractive face wears off in the long run and is attenuated by professionalism in the relationship. Moreover, Gheorghiu et al. [2017] find that, while perceived attractiveness boosts interest and can be valuable in communication, an attractive youthful face is associated with perceived lower quality for the face owner in a scientific/quantitative field, which would inhibit the formation of a positive feedback effect for *ATTRACT*.[6]

The strength of the perception effects is also likely to vary across situational contexts, such as the frequency of face-to-face social interactions with information possessors. Culture, gender stereotypes, and disclosure regulation may also modulate the impression effects. We examine various additional tests for these effects.

Using a large sample of 248,523 quarterly earnings per share (EPS) forecasts and 7,038 analyst-year observations, we first examine the associations of the face factors with analysts' forecast accuracy. We find that analysts with the highest *TRUST* and *DOM* scores produce earnings forecasts that are 3.15% and 6.65% more accurate than analysts with the lowest *TRUST* and *DOM* scores, respectively. These effects are economically meaningful, correspond to 4.4%–9.3% of the standard deviation of accuracy, and are comparable to other significant determinants of forecast accuracy documented in previous studies, such as prior industry-related experiences (Bradley, Gokkaya, and Liu [2017]) and *fWHR* (He et al. [2019]).

To focus on the importance of the social interaction channel for the impression effects, we test whether the relation between impression and accuracy is stronger when analysts have recently attended events hosted by firms or brokerage houses. These events facilitate in-person encounters between

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[5] Langberg and Sivaramrishnan [2010] suggest that managers believe they can learn from analysts. If so, the managers are more likely to share information with analysts they perceive as more competent. Studies also show that observers are more attentive to dominant faces (Maner et al. [2008]) or are more responsive to gaze cues from dominant faces (Jones et al. [2010]). All these factors suggest that high-*DOM* analysts are more likely to succeed in getting information from managers and other information possessors.

[6] Research on the feedback effects of face impressions is nascent, and the underlying mechanisms are currently being explored by social psychologists. For example, Jaeger, et al. [2020] study the persistence of the effect of the trustworthiness impression.

analysts and information possessors such as firm managers and industry experts. We find stronger positive relations between *TRUST* and accuracy as well as *DOM* and accuracy within the 180-day post-event window. The evidence is consistent with our hypothesis that perceptions about analysts' traits derived from social interactions affect the analyst's ability to obtain information and consequently, to attain high forecast accuracy.

We also consider an important regulatory change to information access via social interactions, specifically Regulation Fair Disclosure (Reg FD), which the Securities and Exchange Commission (SEC) introduced in October 2000 to curb selective access of analysts to firm managers. We find that the coefficient of *TRUST* is highly significant pre-Reg FD but is substantially smaller and statistically insignificant post-Reg FD. This suggests that leveling the playing field with the regulatory change negates the preferential access advantage enjoyed by the trustworthy-looking analysts pre-Reg FD. *DOM* is highly significant post-Reg FD, which suggests that analysts' being perceived as competent may open opportunities for access to information from nonfirm sources such as industry experts and analyst peers. Having such alternative sources became advantageous post-Reg FD when access to firm information became equalized.

We turn next to examine how perception effects may vary across different situational contexts. First, we investigate whether the relation between face factors and accuracy varies between new and seasoned analysts and new and seasoned CEOs/CFOs. As explained earlier, we expect the effect of *ATTRACT* to be more short-lived relative to the other two factors. Consistent with this, we find that *ATTRACT* is positively associated with forecast accuracy for new analysts and in firms with new CEOs/CFOs, but not for seasoned analysts or seasoned top officers. In contrast, the effects of *TRUST* and *DOM* are long-lasting, consistent with possible self-fulfilling feedback effects.

Evolutionary theory suggests that being perceived as trustworthy is especially beneficial for survival in high-threat environments (Oosterhof and Todorov [2008]), so we examine the face factor–accuracy relation in high-uncertainty environments. Consistent with adaptive evolutionary theory, we find that the sensitivity of forecast accuracy to *TRUST* is higher in firms with higher earnings volatility and in firms with higher analyst forecast dispersion.

We turn to consider the capital market implications from face factors to understand impression associations with information dissemination by analysts. Face impressions about analysts may influence their capital market clients' attention and their clients' perceptions of the quality of their information.[7] For example, clients who perceive an analyst as competent, honest, or likable may be more attentive and credulous about the analyst's

[7] Brownlow and Zebrowitz [1990] find that the facial appearance of television spokespersons affects the audience's perception of information quality. Gheorghiu et al. [2017] find that the facial appearance of scientists affects the communication of scientific findings to the

information and therefore react more strongly. Consistent with this, we find stronger stock return reactions to forecast revisions of higher *TRUST* analysts, all else equal. The three-day return response coefficient to earnings forecast revision is 6.23% higher than the baseline for a one-standard-deviation increase in analyst *TRUST*.

Institutional investors are much more likely than retail investors to have face-to-face meetings with analysts.[8] This suggests that face impressions will have a stronger effect on institutional investors. Consistent with this, we find that the *TRUST*–stock return sensitivity relation is indeed stronger in firms with high institutional ownership. Overall, the results on capital market effects are consistent with our hypothesis that face impressions of financial analysts by capital market participants influence equilibrium asset prices.

Finally, we examine gender differences for the face factor associations with accuracy and All-Star status. The psychology literature finds that face impressions that do not match societal norms of gender stereotypes tend to elicit strong negative reactions from the observers (Oh, Buck, and Todorov [2019], Oh et al. [2020]). Consistent with this, we find that, while female analysts on average provide more-accurate forecasts than male analysts,[9] high-*DOM* female analysts are significantly less accurate than their male counterparts. We also find lower accuracy for more attractive female analysts. The study of Gheorghiu et al. [2017] on the communication of scientific research to the public finds that attractiveness decreases the perceived quality of the findings. Thus, attractiveness may especially disadvantage female analysts' access to information.

Emery and Li [2009] infer from their study that All-Star membership is a popularity contest. As institutional clients and analyst peers vote on All-Star status, face impressions may influence selection. Consistent with this idea, we find a striking gender difference in the face impression associations: high *DOM* increases All-Star status likelihood by 25.4% for male analysts but *reduces* it by a whopping 67.7% for female analysts. The perception of higher masculinity as indicated by a high *DOM* score violates the female stereotype, which Oh et al. [2019, 2020] suggest dominant-looking female analysts are perceived as less likable and thus less likely to be voted an All-Star. The stark difference in the *DOM* effect between female and male analysts for forecast accuracy and career outcomes suggests the possible presence of gender discrimination in the financial analyst labor market.

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public through two key channels—selection (which research the public chooses to find out about) and evaluation (the opinions they form about that research).

[8] The literature suggests that face-to-face interactions with analysts and investors occur during private meetings (Soltes [2014], Solomon and Soltes [2015]), corporate site visits (Cheng et al. [2016]), and analyst/investor days (Kirk and Markov [2016]). Additionally, many analyst reports provide photos of the analysts, enabling face impressions to be formed by institutional investors who are likely subscribers to the reports.

[9] The result is consistent with Kumar [2010], who argues that high-ability females self-select to enter the analyst profession, which has been traditionally dominated by males.

In our empirical tests, we are as careful as possible to rule out alternative explanations. We control for a rich set of characteristics about the analyst, firm, and brokerage house, and we include different fixed effects. We examine robustness using alternative measures for face factor scores and forecast accuracy and using alternative selection procedures for the photographs. We also consider the following: representativeness of the LinkedIn photographs, the possibility that the photographs are edited or stale, and the nonlinear effects of age on face impressions. We also provide a calibration of measurement errors in the face factor scores relative to human ratings. Overall, our evidence is consistent with the hypothesis that observers' impressions of an analyst, derived from reading the analyst's face, influence their willingness to share information with the analyst and their credulity about the information in the analyst's reports.

An important caveat in interpreting our results is that we construct the face factors using social psychology models explicitly developed to capture *perceptions* about character traits, which do not necessarily match *actual* character traits. These perceptions may or may not be correct, and the psychology literature has explicitly cautioned against using the perception measures to predict specific personality characteristics (Todorov [2017]).[10] Although obvious misperceptions may be corrected over time, initial perceptions may generate self-fulfilling prophecies or feedback effects. This means that different kinds of data would be needed to disentangle the effects of underlying traits from the effects of impressions. At the very least, evidence about the transient nature of some impressions and the striking gender differences suggest that before identifying perception-based face factors with inherent and durable actual character traits, extreme caution should be exercised.[11,12]

Our study contributes to several strands of literature. A growing literature in economics, finance, and accounting documents the importance of face-based inferences. Two studies in accounting use a measure derived from specific physical face features, *fWHR*, to identify personality traits and find that *fWHR* is strongly associated with corporate misreporting and analyst

[10] Todorov [2017, p. 117] writes that trying to predict a specific personality trait from a person's face approaches "audacity verging on insanity." Our evidence does not justify selection of analyst job candidates by brokerage company recruiters using face factors.

[11] Related to this, both Jia et al. [2014] and He et al. [2019] are very careful to acknowledge that using fWHR to instrument for underlying personality traits is controversial in the neuroscience and psychology literature. See chapters 9 and 10 in Todorov [2017] for a discussion of the related scientific studies and issues with fWHR as a measure for personality traits. Therefore, the matter has not been definitively settled, and this field is subject to ongoing research and debate.

[12] There has been growing interest in applying AI machine learning technology to business applications. For example, as of October 2019, more than 100 employers, including Hilton and Unilever, use a proprietary AI-driven interview assessment system developed by HireVue, which has analyzed more than a million job seekers. Our study provides important insights to capital market participants who need to understand the nature of the information that AI extracts, its consequences, and its limitations for the proper use of the technology.

site visit activities (Jia et al. [2014], He et al. [2019]). Our face factor measures have a low correlation with *fWHR*, and our findings for the face factors are incremental to the effects of *fWHR*. To the extent that *fWHR* captures the role of analyst effort and testosterone-induced behaviors, our measures' incremental power is more likely to capture the impression effects.

Our study also contributes to the literature on the determinants of sell-side analyst performance and the capital market consequences of analyst output.[13] Survey evidence in Brown et al. [2015] indicates that private communications between analysts and management are more useful than analysts' independent research for analysts' accuracy. We add to this literature by showing that face-based trait impressions from analysts' social interactions are associated with analysts' performance and career outcomes. In this way, our paper also contributes to the emerging literature on the relevance and importance of social cognition and social interactions in economic decision-making.[14] Drawing from social psychology research, Schneider [2005]) and Bordalo et al. [2016, 2019] argue that beliefs respond to social stereotypes, and they propose a "social cognition approach" to model stereotypes. Our study provides evidence that trait inferences from social interactions are strongly associated with essential economic outcomes and differ by gender.

Finally, after the pioneering study of Becker [1971] on the economics of discrimination, interest has grown in economics-based literature on gender discrimination in the corporate world.[15] The related psychology literature finds that women, more than men, are expected to display warmth, empathy, and altruism (Kite, Deaux, and Haines [2008], Ellemers [2018], Mast and Kadji [2018], Bordalo et al. [2019]). Our finding of a striking gender penalty on analysts' performance and career outcomes for females who give an impression of dominance contributes to the literature on gender stereotypes.

[13] This literature has shown the relevance of analyst experience, political views, portfolio complexity, prestige of the analysts' brokerage house, and the analysts' industry experience to their performance (Clement [1999], Gilson et al. [2001], Malloy [2005], Kumar [2010], Gunn [2014], O'Brien and Tan [2015], Jiang, Kumar, and Law [2016], Bradley et al. [2017], Merkley, Michaely, and Pacelli [2020]). Womack [1996] documents significant market reactions to analysts' revisions of recommendations, and Hong, Lim, and Stein [2000] find that analysts' firm-specific information explains price momentum.

[14] See, for example, Duflo and Saez [2003], Shive [2010], Kaustia and Knüpfer [2012], Shiller [2000, 2017], and Hirshleifer [2020].

[15] Goldin and Rouse [2000] examine hiring discrimination against women. Bertrand, Goldin, and Katz [2010] analyze the differences in career dynamics between female and male MBA graduates. Heilman [2012] describes how gender stereotypes lead to biased evaluative judgments and discriminatory treatment of women in workplaces. Bigelow et al. [2014] show, in an experimental setting, that subjects consider IPOs led by female founders to be less attractive. Newton and Simutin [2015] document wage inequality between genders. Adams and Kirchmaier [2016] document the low female presence on corporate boards. Niessen-Ruenzi and Ruenzi [2019] find that female-managed funds attract significantly lower inflows than funds managed by their male peers, despite similarities in performance.

2. Data

Our sample consists of U.S. sell-side analysts and the firms they cover in the merged CRSP/Compustat data set from January 1990 to December 2017. We obtain the full name and brokerage house affiliation of sell-side analysts responsible for the EPS forecasts using the I/B/E/S detailed history recommendation database and Thomson Reuters Investext. Next, we extract analysts' photographs and demographic information from their LinkedIn profile page.[16] Of the 4,511 sell-side analysts in Thomson Reuters Investext during 1990–2017, 1,566 maintained a LinkedIn profile as of May 2018, and 795 posted a profile picture. We obtain quarterly forecasts for each identified analyst and the relevant regression variables for firms they follow from Compustat and CRSP. Our final merged sample consists of 248,523 quarterly EPS forecasts and 7,038 analyst-year observations for 5,847 unique firms. Table A1,A2 describes measures of all key variables and controls.

The analyst domain has important advantages for investigating psychological effects arising from social interactions on capital market outcomes. Given analysts' role as information intermediaries between firms and investors, social interactions are critical avenues for analysts to obtain and communicate private information about the firms they follow (e.g., Soltes [2014], Bradshaw [2012], Ke and Yu [2006], Brown et al. [2015], and Chen, Mayew, and Yan [2018]).[17] How analysts are perceived in their social interactions with information providers such as firm managers, firm suppliers, firm customers, industry experts, and analyst peers likely affects analysts' access to information, and their credibility with investor clients also depends on how those clients perceive them. The analyst setting also provides data availability and measurability advantages. Adequate high-frequency data exist for objectively measurable benchmarks for analyst outcomes such as forecast accuracy and career advancement over a sufficiently long time. Control variables associated with firm and analyst characteristics are also available, so we are better able to identify the incremental contributions of the key face factors in explaining analyst behaviors and outcomes over fi alternatives.

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[16] We perform a manual check to ensure that the name and past or current job title on LinkedIn match the data on Investext to ensure we have selected the right analyst.

[17] Soltes [2014] shows the importance of social interactions for financial analysts by finding that analysts acquire information from private meetings with management. Similarly, Bradshaw [2012], Ke and Yu [2006], and Brown et al. [2015] document that "access to management" is an important channel through which analysts gather information. In addition, Chen, Mayew, and Yan [2018] find that analysts sharing the same office with local peers and who are therefore more likely to interact with them produce more-accurate earnings forecasts and generate stronger stock market responses.

2.1 FACE FACTORS

When exposed to a face, human observers form judgments about a wide range of traits, including approachability, aggression, age, trustworthiness, confidence, intelligence, and dominance.[18] The seminal research of Oosterhof and Todorov [2008] using computer modeling suggests that the multitude of traits can be described sufficiently along two key dimensions, one associated with trustworthiness and the other associated with dominance. Extending this research, Sutherland et al. [2013] add attractiveness as a third dimension and report that the three factors together capture 72% of the variation in 13 categories of first impressions formed from observing faces.[19] As discussed in section 1, these impressions are likely products of natural and sexual mating selection in evolutionary history that aided the survival of the species (see, e.g., Buss and Schmitt [1993], Thornhill and Gangestad [1999], Fink, Neave, and Seydel [2007], Oosterhof and Todorov [2008], Todorov, Baron, and Oosterhof [2008], Todorov, Pakrashi, and Oosterhof [2009], Zebrowitz et al. [2010], Little, Jones, and DeBruine [2011]). Vernon et al. [2014] show that a linear neural network ML method that estimates these face factors for a large sample of photographs outperforms various alternative ML techniques.[20]

We first preprocess the analysts' photos to standardize the size and head location and then apply the facial recognition software, IBUG,[21] to each photo to delineate the 68 fiducial landmark points. We construct 65 physical face features from the coordinates of these points. Then, we calculate the raw factor scores (*TRUST_Raw*, *ATRACT_Raw*, *DOM_Raw*) from these 65 attributes using Vernon et al. [2014] ML model weights. Last, we

[18] See, for example, Boothroyd et al. [2007], Oosterhof and Todorov [2008], and Walker and Vetter [2009].

[19] The 13 first impressions are: aggression, approachability, trustworthiness, smile, confidence, health, attractiveness, age, babyfacedness, dominance, sexual dimorphism, intelligence, and skin. *TRUST* has the highest loadings from approachability, trustworthiness, and degree of smile. *ATTRACT* has the highest loadings from attractiveness, health, and babyfacedness. *DOM* has the highest loadings from dominance, sexual dimorphism, and confidence. See Sutherland et al. [2013] for details. The Vernon et al. [2014] model uses initial impressions on 16 personality traits.

[20] Vernon et al. [2014] labels as "approachability" what Sutherland et al. [2013] and Oosterhof and Todorov [2008] refer to as "trustworthiness/valence." We use "trustworthiness" as a shorthand label to follow convention. 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 scores by human raters, with statistically significant average correlation coefficients equal to 0.9, 0.7, and 0.67 for trustworthiness, attractiveness, and dominance, respectively.

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

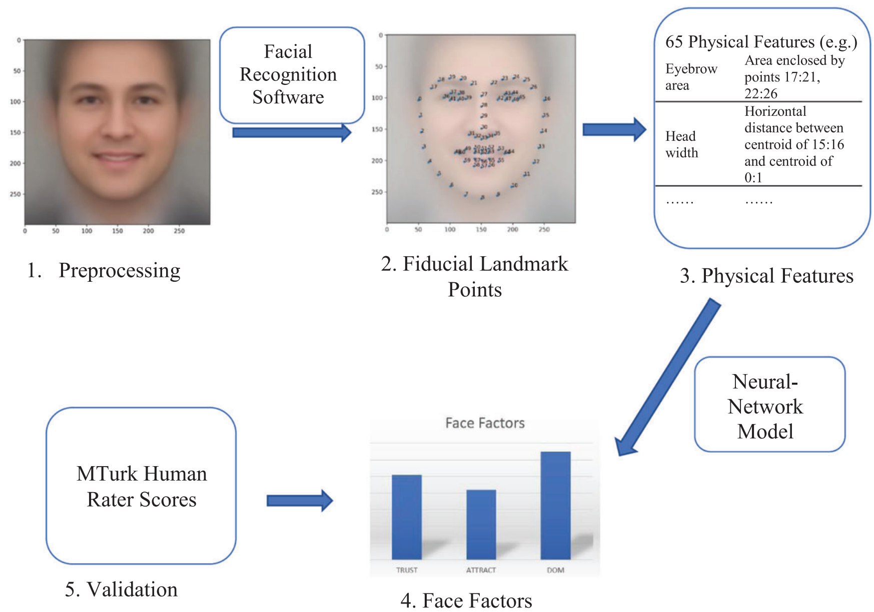

FIG. 1.—Face factors extraction procedure. We describe the procedures used to extract trait factor scores using analysts' profile photos as inputs:
1) Preprocessing: We standardize the size of the photo to 200 px × 200 px, adjust the orientation, and locate the head area in the center.
2) Fiducial landmark points: We apply the automated facial point annotation tool (IBUG) to delineate 68 fiducial landmark points and obtain the corresponding 2D coordinates for each photo.
3) Physical features: Based on table S1 of Vernon et al. [2014], we use the coordinates of the 68 fiducial landmark points to construct 65 physical features. See table 1 of the online appendix for the mapping from landmark points to physical attributes.
4) Face factors: We apply the neural network model of Vernon et al. [2014] and use the 65 physical features to obtain the raw face factor scores. Figure 1 in the online appendix provides an illustration of synthesized faces with varying trait scores.
5) Validation: We select a random sample of 100 analyst photos and ask five male and five female raters from Amazon Mechanical Turk to rate the photos along the three trait dimensions on a 1–7 Likert scale. We reshuffle the order of photos and ask the rater to view the photo for at least 10 seconds before selecting the rating.

validate these scores with MTurk human raters. Figure 1 illustrates how photos are processed to obtain face factors.[22]

[22] Vernon et al. [2014] construct the 65 physical features using 179 fiducial points that are manually labeled with the PsychMorph software. They validate the neural network model in two ways. First, they apply a 10-fold cross-validation method in which a random eight-tenths of the sample are used for training and the other two-tenths are used for out-of-sample validation; they repeat the procedure 100 times and obtain average correlations between the machine-generated scores and the human scores of 0.67–0.90. Second, they use the ML model to generate synthesized face-like images and ask human raters to rate the impressions along the three dimensions and obtain correlations between 0.56 and 0.93.

Psychology literature (e.g., Olivola and Todorov [2010], Oh, Buck, and Todorov [2019]) finds significant differences in perceived impressions by gender. To facilitate comparison across the face factors and allow for differences in impressions by the gender of the observed, we scale the raw scores between 0 and 1 by gender group. We label the within-gender scaled face factors as *TRUST*, *ATTRACT*, and *DOM*.

2.2 ANALYST FORECAST ACCURACY AND CAREER OUTCOMES

We define analyst performance as relative forecast accuracy with the mean forecast accuracy of other analysts following the firm as the benchmark. We estimate it as the negative proportional mean absolute forecast error, *PMAFE*, and it is calculated as the difference between the absolute forecast error of analyst i for firm j in quarter t, AFE_{ijt}, from its firm-quarter I/B/E/S sample mean, $MAFE_{jt}$, scaled by $MAFE_{jt}$ (Clement [1999]). Scaling by $MAFE_{jt}$ controls for firm × quarter level common variations in forecast errors and reduces heteroskedasticity (Ke and Yu [2006]).[23] For analyst career outcomes, we assign a value of 1 to the I_{STAR} variable for analyst-years based on *Institutional Investor* magazine's All-Star Analyst list from 1991 to 2017, and 0 otherwise.

2.3 CONTROL VARIABLES

Using information from analysts' LinkedIn profiles, we estimate *AGE* by assuming the analyst began college at 19, and we assign *GENDER* following the gender list of first names in the Behind the Name database, with help from FaceX software for unisex or unlisted names.[24] We measure analysts' facial width-to-height ratio, *fWHR*, from their LinkedIn profile picture (Lefevre et al. 2013).[25]

We include a large set of additional controls for analyst, firm, and brokerage house characteristics following past studies on analyst forecast accuracy (Clement [1999], Bradley et al. [2017]). They include: a *TOP10* indicator for analysts affiliated with a top 10% brokerage house as measured by the number of analysts; *BROKER_SIZE*, representing the number

[23] See also Malloy [2005], De Franco and Zhou [2009], Green et al. [2014], and Bradley et al. [2017]. We retain the most recent quarterly earnings forecast issued by a given analyst and exclude the analyst's own forecast from the *MAFE* calculations. Results are robust to alternative accuracy measures using negative absolute forecast error *AFE* (table A4).

[24] The National Center for Education Statistics reports that from 1970 to 2017, 53% to 69% of students enrolled in full-time degree-granting postsecondary institutions were aged between 18 and 21; see https://nces.ed.gov/fastfacts. Behind the Name, https://www.behindthename.com, collects gender and name usage history from the Social Security Administration and other sources. For the three unisex first names and 45 names not found in the Behind the Name database, we determine the gender using FaceX's face analytics API (https://facex.io/). This procedure classified the 48 analysts as 46 males and two females with a confidence level of 99.3% or higher.

[25] *fWHR* is the distance from the left to right zygion relative to the distance from the upper lip to the highest point of the eyelids. All in their raw values, *fWHR* correlations with *TRUST*, *ATTRACT*, and *DOM* are 0.44, –0.07, and 0.09, respectively, all significant at the 5% level.

of analysts employed by the brokerage; general experience *GEXP* and firm-specific experience *FEXP* to represent the numbers of years since an analyst first appeared in the I/B/E/S and since the analyst's first forecast of the firm, respectively; *HORIZON* for the number of days between the forecast issue date and the earnings announcement date; and *PORTFOLIO_SIZE* and *SIC2* for the number of firms and number of two-digit SIC industries an analyst covers, respectively, to capture analyst business/job complexity. The controls are mean-adjusted using the corresponding I/B/E/S firm-quarter mean to remove common variations at the firm × quarter level (Clement [1998, 1999]) and are labeled *DAGE*, *DGEXP*, *DFEXP*, *DTOP10*, *DSIC2*, and *DHORIZON*.[26] I_{FEMALE} is an indicator equal to 1 for female analysts, and 0 otherwise. *MEAN_ACCURACY* is the analyst's mean *ACCURACY* for the year.

Firm-level controls *SIZE* and *BM* are the logarithm of a firm's market capitalization and book-to-market ratio, measured at the end of the month before the earnings forecast. *ANALYST_FOLLOWING* is the number of analysts following the firm in the given quarter. RET_{6m} 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 reduce the influence of outliers.

Table 1, panel A, provides descriptive statistics of the main variables. The analyst-level mean scores for *TRUST_Raw*, *ATTRACT_Raw*, and *DOM_Raw* are 0.21, 0.06, and 0.16, respectively, with substantial variation across analysts. Of the 795 analysts in the sample, 101 or 12.7% are female,[27] and females have higher trustworthiness and attractiveness scores and lower dominant scores relative to male peers. The average forecast *ACCURACY* is 2.404%, and the average firm has a market value of USD 2.65 billion (= $e^{14.75}$), a *BM* of 0.53, and is covered by 15.69 analysts. Every year, the average analyst has a 7.6% probability of being an All-Star Analyst, has an annual mean forecast accuracy of 0.6%, covers a portfolio with a total market capitalization of USD 31.6 billion (= $e^{17.27}$), and is affiliated with a brokerage house with 73.68 analysts.

Panel B shows the pairwise Pearson correlations for the analyst-level variables.[28] The panel shows that *Face Factors* are correlated with each other and with gender, consistent with Oosterhof and Todorov [2008], Sutherland et al. [2013], and Vernon et al. [2014]. Attractiveness and dominance have strong negative correlations, so when we include all three variables in a single regression to provide evidence about their relative relevance, we use orthogonalized *Face Factors* following the modified Gram–Schmidt process

[26] Robustness checks in table A4, column 7, consider control variables without firm × quarter mean adjustments; the regression includes firm- and year-fixed effects instead.

[27] The percentage of female analysts in our sample is comparable to the survey results of Green et al. [2009], which show that the representation of female sell-side analysts was between 14% and 16% of all analyst positions in the United States between 1994 and 2005.

[28] Table A2 reports the pairwise correlations for the forecast-level variables.

TABLE 1
Summary Statistics

Variables	N	Mean	SD	P10	P25	Median	P75	P90
Panel A: Summary statistics								
Analyst characteristics								
TRUST	795	0.596	0.174	0.361	0.460	0.624	0.726	0.804
ATTRACT	795	0.536	0.133	0.369	0.453	0.537	0.620	0.705
DOM	795	0.657	0.118	0.512	0.595	0.665	0.730	0.799
fWHR	795	0.438	0.162	0.226	0.318	0.430	0.551	0.656
TRUST_Raw	795	0.208	0.336	−0.247	−0.062	0.255	0.463	0.621
ATTRACT_Raw	795	0.055	0.257	−0.264	−0.104	0.050	0.216	0.375
DOM_Raw	795	0.160	0.235	−0.145	0.027	0.170	0.317	0.451
fWHR_Raw	795	2.155	0.181	1.911	2.031	2.150	2.273	2.393
I_{FEMALE}	795	0.127						
Male subsample								
TRUST_Raw	694	0.195	0.330	−0.247	−0.066	0.244	0.441	0.597
ATTRAC_Raw	694	0.033	0.246	−0.283	−0.125	0.029	0.184	0.350
DOM_Raw	694	0.182	0.225	−0.104	0.056	0.194	0.330	0.457
Female subsample								
TRUST_Raw	101	0.296	0.363	−0.265	−0.033	0.395	0.591	0.674
ATTRACT_Raw	101	0.208	0.283	−0.154	−0.003	0.236	0.390	0.571
DOM_Raw	101	0.007	0.252	−0.311	−0.161	−0.003	0.158	0.325
Forecast characteristics								
ACCURACY	248,523	2.404	71.216	−77.778	−24.138	8.108	46.619	93.954
DTOP10	248,523	0.036	0.447	−0.606	−0.440	0.214	0.400	0.514
DGEXP	248,523	0.213	5.039	−5.988	−3.197	−0.012	3.164	6.897
DFEXP	248,523	0.013	2.917	−3.325	−1.630	−0.089	1.165	3.549
DAGE	248,523	0.000	6.131	−7.500	−3.000	0.000	2.333	7.667
DHORIZON	248,523	−1.874	54.418	−59.970	−34.000	−8.471	15.889	69.625
DPORTFOLIO_SIZE	248,523	0.298	6.238	−6.333	−3.297	−0.200	3.250	7.278

(*Continued*)

TABLE 1—*(Continued)*

Panel A: Summary statistics

Variables	*N*	Mean	SD	P10	P25	Median	P75	P90
DSIC2	248,523	0.018	1.503	−1.632	−0.833	−0.125	0.714	1.810
SIZE	248,523	14.747	1.656	12.544	13.550	14.761	16.014	17.101
BM	248,523	0.530	0.936	0.105	0.217	0.383	0.636	0.989
RET_{6M}	248,523	−0.012	0.286	−0.325	−0.167	−0.027	0.112	0.284
ANALYST_FOLLOWING	248,523	15.687	9.507	5.000	8.000	14.000	21.000	29.000
Analyst characteristics (analyst-year level)								
I_{STAR}	5,717	0.076						
MEAN_ACCURACY	5,717	0.006	0.308	−0.274	−0.151	−0.029	0.106	0.293
BROKER_SIZE	5,717	73.683	61.400	50.236	2.000	25.000	57.000	89.559
PORTFOLIO_CAP	5,717	17.269	1.527	14.007	16.306	17.588	18.479	19.013
Market reaction characteristics								
CAR[−1, +1]	85,643	−0.001	0.072	−0.065	−0.025	−0.001	0.024	0.064
REVISION	85,643	−0.000	0.014	−0.011	−0.003	0.001	0.003	0.009
$I_{HIGH\ INST}$	85,643	0.350						

Panel B: Pearson correlations (analyst-year level)

	TRUST_Raw	*ATTRACT_Raw*	*DOM_Raw*	I_{FEMALE}	*fWHR*
ATTRACT_Raw	0.045**				
DOM_Raw	−0.090**	−0.511**			

(Continued)

TABLE 1—*(Continued)*

Panel B: Pearson correlations (analyst-year level)

	TRUST_Raw	*ATTRACT_Raw*	*DOM_Raw*	I_{FEMALE}	*fWHR*
I_{FEMALE}	0.149**	0.255**	−0.246**		
fWHR_Raw	0.462**	−0.032**	0.029**	−0.046**	
AGE	−0.035**	−0.011	0.066**	−0.006	0.017

This table summarizes the main variables (panel A) and the pairwise Pearson correlation matrix (panel B). At the analyst level, *TRUST*, *ATTRACT*, and *DOM* correspond to the orthogonalized factors of trustworthiness, attractiveness, and dominance, scaled to [0, 1] within gender, respectively. *fWHR* is the analyst's facial width-to-height ratio scaled to [0, 1] within gender. *TRUST_Raw, ATTRACT_Raw, DOM_Raw*, and *fWHR_Raw* are the corresponding raw scores. I_{FEMALE} is an indicator that equals 1 if the analyst is a female, and 0 otherwise. The following are forecast-level measures. *ACCURACY* (in %) is the negative value of the proportional mean absolute forecast error. *AGE* is the age of the analyst at the forecast date. *TOP10* is an indicator variable that takes a value of 1 if an analyst is affiliated with a top 10 brokerage house, and 0 otherwise; general experience (*GEXP*) and firm-specific experience (*FEXP*) are the number of years since an analyst appeared in I/B/E/S and from the analyst's first forecast of the firm, respectively; *HORIZON* is the number of days between the forecast date and the earnings announcement date; and *PORTFOLIO_SIZE* and *SIC2* refer to the numbers of firms and two-digit SIC industries an analyst covers, respectively. These control variables are mean-adjusted by subtracting the corresponding mean values across all I/B/E/S analysts covering the firm over the same quarter and denoted as *DAGE, DTOP10, DGEXP, DFEXP, DPORTFOLIO_SIZE, DSIC2*, and *DHORIZON*. Firm-level variables include: *ANALYST_FOLLOWING*, the number of analysts following a firm; *SIZE*, the natural log of market capitalization; *BM*, the book-to-market ratio of the firm, and RET_{6m}, the prior six-month market-adjusted buy-and-hold returns. I_{FEMALE} is an indicator variable taking a value of 1 if the analyst is female, and 0 otherwise. Annual-level variables include: *BROKER_SIZE*, the size of the brokerage house that an analyst is affiliated with, measured by the number of analysts it employs; I_{STAR}, an indicator variable equal to 1 if an analyst is elected an All-Star Analyst in the year, and 0 otherwise; *MEAN_ACCURACY*, the analyst's mean *ACCURACY* for the year, and *PORTFOLIO_CAP*, the logarithm of the total market capitalization of firms that an analyst covers. Additional summary statistics and a correlation matrix are available in table A2.*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

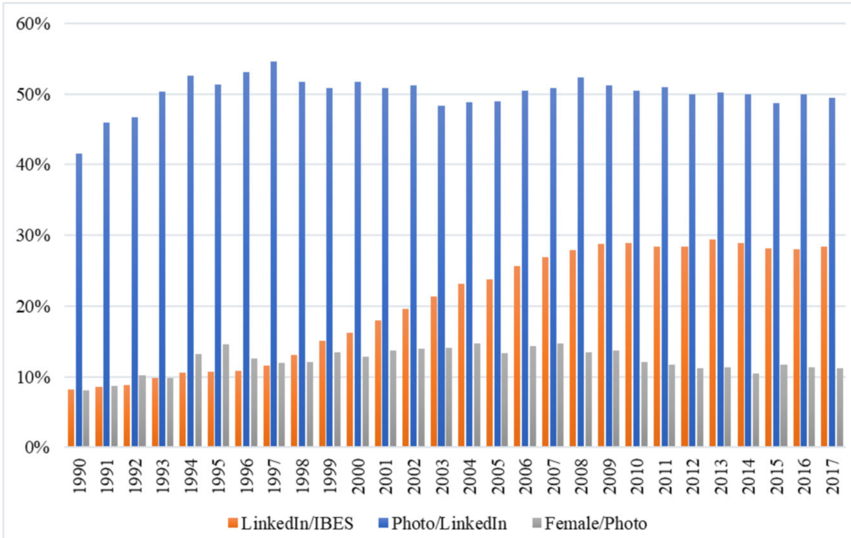

FIG. 2.—Sample coverage ratio of analysts on LinkedIn and analysts with profile photos. This figure plots the sample coverage ratio over time. The blue bar plots the fraction of analysts who have registered on LinkedIn relative to analysts in the I/B/E/S-Compustat-CRSP merged data set. The red bar plots the fraction of LinkedIn analysts with profile photos. The gray bar plots the fraction of females among the LinkedIn analysts with photos.

(Van Loan and Golub [1996]).[29] Female analysts have significantly higher attractiveness and trustworthiness scores and lower dominance scores, so as noted earlier, the *Face Factors* are standardized within gender samples.

2.4 SAMPLE REPRESENTATIVENESS

We compare our final sample with LinkedIn analysts without photos and I/B/E/S analysts to understand the representativeness of our sample. Evidence in table A3 shows that our LinkedIn analysts-with-photo sample has characteristics similar to the LinkedIn sample without photos, which alleviates potential bias concerns from self-selection of photo inclusion in our test sample. Comparing our LinkedIn with-photo sample and the I/B/E/S population, the analysts in our test sample are more experienced and more important players in the analyst industry.[30] Figure 2 illustrates the sample coverage ratio over the sample period. The fraction of I/B/E/S analysts on LinkedIn gradually increased from less than 10% in 1990 to about 28% in

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[29] We use the following orthogonalization order (Vernon et al. [2014]), from first to last: trustworthiness—attractiveness–dominance. We scale the orthogonalized variables to be between 0 and 1. We obtain similar results without orthogonalization or when we use alternative ordering in robustness tests in section 6.

[30] Table A3, panel A, shows that from 2010 to 2017, when LinkedIn gained popularity, 1,139 of 4,343 I/B/E/S analysts (26%) maintained a LinkedIn profile and 582 (51% of LinkedIn sample) included a picture in their profiles.

2007 and has leveled since, and the proportion of LinkedIn analysts with a profile photo remained steady over the sample period.[31]

3. *Face Factors and Analyst Forecast Accuracy*

In this section, we investigate the association between analyst face factors and the accuracy of analysts' earnings forecasts. We start with a baseline specification and then explore the relative relevance of impressions that arise in different situations reflecting variations in social interactions. We consider situations including recent face-to-face meetings between the analysts and the firm insiders, different disclosure regulatory regimes, when analysts are new to the industry or when the CEO/CFO is new, and those arising from differences in firm fundamental uncertainty. Evidence of how the perception-accuracy relation changes across these different social interaction contexts helps to provide insights about the channel through which impressions affect analyst behavior.

3.1 BASELINE ANALYSES

For the baseline estimation of the relation between face factors and forecast accuracy, we regress *ACCURACY* on *Face Factors* using the quarterly forecast-level panel regression:

$$ACCURACY_{i,j,t} = \beta_0 + \beta_1 Face\ Factors_i + \gamma X + \varepsilon_{i,j,t}, \qquad (1)$$

where *Face Factors* are *TRUST*, *DOM*, and *ATTRACT*. The controls in X are firm, analyst, and brokerage house characteristics measured annually at the end of the preceding year.[32] We include firm fixed effects and year fixed effects to control for unobservables that vary across firms or time. We report t-statistics using standard errors clustered by firm in all forecast accuracy regressions.[33]

Table 2 reports the regression results in columns 1–3 for the individual *Face Factors* and in column 4 for all three orthogonalized *Face Factors* jointly. The results indicate that *TRUST* and *DOM* are significantly and positively related to forecast accuracy, but not *ATTRACT*. Column 4's *Face Factors* coefficients (in %) imply that forecasts are 3.15% and 6.65% more accurate, comparing the most to the least trustworthy-looking and dominant-looking analysts, respectively. These magnitudes are economically meaningful, correspond to 4.4%–9.3% of the standard deviation of *ACCURACY* (71.2%), and are comparable or exceed the 1.55%–3.58% magnitudes for prior

[31] We exclude analyst IDs in I/B/E/S with less than 20 EPS forecasts during the sample period, which corresponds to the bottom two percentile of I/B/E/S analysts.

[32] The control variables include *fWHR*, I_{FEMALE}, *ANALYST_FOLLOWING, DTOP10, DPORTFOLIO_SIZE, DSIC2, DGEXP, DFEXP, DAGE, DHORIZON, SIZE, BM*, and RET_{6M}. See subsection 2.3 for detailed descriptions.

[33] Our results remain robust when clustering standard errors either by analyst or two-ways by firm and year. Subsection 6.1 discusses the results.

TABLE 2

Baseline Regression: Face Factors and Analyst Forecast Accuracy

	(1)	(2)	(3)	(4)
TRUST	3.266**			3.151**
	(2.42)			(2.26)
ATTRACT		−2.058		−2.004
		(−0.91)		(−0.88)
DOM			7.909***	6.647***
			(3.47)	(3.09)
fWHR	3.423**	3.585**	3.790**	3.587**
	(2.02)	(2.08)	(2.21)	(2.09)
I_{FEMALE}	1.864***	1.884***	2.064***	1.875***
	(2.66)	(2.69)	(2.94)	(2.66)
ANALYST_FOLLOWING	0.195***	0.192***	0.186***	0.189***
	(3.94)	(3.87)	(3.76)	(3.81)
DTOP10	−0.673	−0.613	−0.627	−0.672
	(−1.35)	(−1.25)	(−1.27)	(−1.36)
DPORTFOLIO_SIZE	0.085**	0.084**	0.092**	0.092**
	(1.98)	(1.97)	(2.16)	(2.16)
DSIC2	−0.794***	−0.784***	−0.777***	−0.786***
	(−4.32)	(−4.25)	(−4.21)	(−4.26)
DGEXP	−0.077	−0.089	−0.099*	−0.087
	(−1.45)	(−1.58)	(−1.82)	(−1.56)
DFEXP	0.278***	0.286***	0.294***	0.287***
	(2.93)	(3.02)	(3.13)	(3.04)
DAGE	−0.072**	−0.074**	−0.085**	−0.083**
	(−1.99)	(−2.04)	(−2.38)	(−2.29)
DHORIZON	−0.302***	−0.302***	−0.302***	−0.302***
	(−51.42)	(−51.40)	(−51.39)	(−51.41)
SIZE	0.075	0.095	0.100	0.082
	(0.19)	(0.24)	(0.25)	(0.21)
BM	−0.034	−0.034	−0.032	−0.034
	(−0.13)	(−0.13)	(−0.13)	(−0.13)
RET_{6M}	−1.074*	−1.072*	−1.082*	−1.085*
	(−1.89)	(−1.89)	(−1.91)	(−1.91)
Adjusted R^2	0.064	0.064	0.064	0.064
N	248,523	248,523	248,523	248,523

This table reports forecast-level panel regressions of analyst forecast accuracy on their face factors. The dependent variable *ACCURACY* (in %) is the relative accuracy of an analyst forecast. The key independent variables are *TRUST*, *ATTRACT*, and *DOM* corresponding to the analyst's face factors of trustworthiness, attractiveness, and dominance, respectively, scaled to [0, 1] within gender. I_{FEMALE} is an indicator variable equal to 1 if the analyst is female, and 0 otherwise. Table 1 defines the set of control variables (*fWHR, ANALYST_FOLLOWING, DTOP10, DGEXP, DFEXP, DAGE, DHORIZON, DSIC2, DPORTFOLIO_SIZE, SIZE, BM*, RET_{6M}). Regressions in columns 1–3 use a single face factor, and column 4 regressions include all three face factors, orthogonalized using the Gram–Schmidt procedure. The sample period is 1990–2017. All regressions include a constant, firm fixed effects, and year fixed effects. The *t*-statistics (presented in parentheses) are computed with standard errors clustered by firm.***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

industry-related experience coefficient of accuracy as reported by Bradley et al. [2017].

The significant coefficient in column 4 for *fWHR* implies a 3.59% increase in forecast accuracy for analysts with the highest *fWHR* over analysts with the lowest *fWHR*, consistent with the 4.7% increase in accuracy as reported in He et al. [2019]. *DOM* and *TRUST* remain highly significant with *fWHR* included, so face factors are distinct and incremental to *fWHR*. Interestingly, the significantly positive coefficient of I_{FEMALE} implies that female analysts are 1.88% more accurate than male analysts. This finding is consistent with the Kumar [2010] contention that only high-ability female analysts self-select into this traditionally male-dominated profession.[34]

In sum, the baseline result establishes that the impressions about analysts' trustworthiness and dominance are positively associated with the analysts' forecast accuracy. We next explore how the relation of *Face Factors* to accuracy varies with situational contexts to provide insights about the social interaction channel for impression effects.[35]

3.2 POTENTIAL INFORMATION ACCESS CHANNEL VIA FACE-TO-FACE MEETINGS

Forecast accuracy depends on access to relevant information. If face impressions from in-person social interactions with firm managers facilitate information access, we expect accuracy to be more strongly associated with *Face Factors* when there are recent in-person meetings. Past studies show that firm-hosted analyst/investor-day events and brokerage-hosted investor conferences facilitate information sharing between firms, analysts, and investors (Bushee, Jung, and Miller [2011], Green et al. [2014], Kirk and Markov [2016]).[36] Therefore, we hypothesize that the association between face factors and analysts' forecast accuracy is stronger after recent meetings, with the association decaying over time.

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[34] 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*) and number of industries (*DSIC2*), which is consistent with Clement [1999] and Bradley et al. [2017]. The coefficients of analysts' age (*DAGE*) are negative, likely because they are positively correlated with analysts' firm-specific experience (*DFEXP*).

[35] The incremental explanatory power (measured as marginal adjusted R^2) of the face factors is 0.0123%, comparable to that of *fWHR* (0.0039%) and firm-experience (0.0135%). As discussed in Clement [1999], because dependent variables and most control variables in the model are adjusted by subtracting firm-quarter means, the R^2 (as well as incremental R^2) is lower than it would be in alternative settings with unadjusted accuracy and controls, for which we discuss the corresponding robustness checks in section 6 and table A4.

[36] Analyst/investor days last from half a day to a day and a half. They feature presentations by firm managers, key operations personnel, firm customers and suppliers, and industry experts, as well as informal meal breaks and cocktail hours to provide analysts, firm management, and major investors an important opportunity for face-to-face interactions. Brokerage-sponsored investor conferences consist of formal company presentations, often moderated by the analyst-host, followed by question-and-answer sessions and sometimes a series of one-on-one meetings between management and select clients. Bushee, Jung, and Miller [2011] show that broker-hosted conferences are important venues for soft information-sharing between managers (and other informed participants) and analysts and investor client groups. Green et al. [2014] find that interactions during broker-hosted conferences are associated with more informative recommendation changes and more accurate and more timely earnings forecasts in the post-Reg FD era. Kirk and Markov [2016] find that analyst/investor days are associated with substantial abnormal absolute returns, stock turnover, and abnormal analyst forecast activities.

TABLE 3

Face Factors and Forecast Accuracy: Role of In-Person Meetings

	I_{MEET} = *Forecasts Issued After Meetings*	
	(1) [0, 180]	(2) [181, 360]
$TRUST \times I_{MEET}$	15.220**	8.610
	(2.41)	(1.38)
$ATTRACT \times I_{MEET}$	−5.123	−12.490
	(−0.60)	(−1.61)
$DOM \times I_{MEET}$	15.750*	10.320
	(1.77)	(0.99)
TRUST	3.170**	3.380**
	(1.97)	(2.10)
ATTRACT	−0.120	0.090
	(−0.09)	(−0.01)
DOM	7.260**	7.360**
	(2.05)	(2.10)
I_{MEET}	−16.210*	−3.400
	(−1.67)	(−0.33)
Controls	Yes	Yes
Adjusted R^2	0.054	0.054
N	197,051	197,051

This table presents panel regression results on in-person meetings and the face factor–accuracy relation. The dependent variable *ACCURACY* (in %) is the relative accuracy of an analyst forecast. *TRUST*, *ATTRACT*, and *DOM* correspond to the analyst's face factors of trustworthiness, attractiveness, and dominance, respectively, orthogonalized and scaled to [0, 1] within gender. We include the same set of control variables as in table 2. I_{MEET} is an indicator variable that equals 1 if the forecast is issued following an investor/analyst day event or investor conference in which the analyst and the corporate managers participated, and 0 otherwise. Columns 1 and 2 correspond to the [0, 180] day and [181, 360] day windows after the events, respectively. We include a constant, firm fixed effects, and year fixed effects. The *t*-statistics (presented in parentheses) are computed with standard errors clustered by firm.***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

We obtain data on analyst/investor days and investor conferences from the Thomson Reuters Street Events database for 2004–2017. We collect the names of participating analysts and firms from event transcripts. We identify analyst-management pairs that attended the same events and assign a value of 1 to the indicator variable, I_{MEET}, if a forecast is issued within 180 days or 360 days after such events, or 0 otherwise. We augment regression model (1) by adding I_{MEET} as a main effect variable and an interaction variable with *Face Factors*:

$$ACCURACY_{i,j,t} = \beta_0 + \beta_1 Face\ Factors_i + \beta_2 Face\ Factors_i \times I_{MEET} + \gamma\ X + \varepsilon_{i,j,t}. \qquad (2)$$

Table 3 presents the results, with columns 1 and 2 corresponding to the [0, 180] day and [181, 360] day post-meeting windows, respectively. The baseline main effect variables for *TRUST* and *DOM* remain positive and significant. The key variables of interest here are *Face Factors* × I_{MEET}, which capture the incremental effect of impressions on accuracy when analysts and information possessors are likely to have met recently. Column 1 shows that both coefficients of $TRUST \times I_{MEET}$ *and* $DOM \times I_{MEET}$ are significantly positive. Economically, the coefficient magnitudes imply that the analysts who look most trustworthy or dominant incrementally improve their forecast accuracy by 15.22% and 15.75%, respectively, when they issue forecasts within the 180 days of attending analyst/investor day events or investor conferences. For comparison, Green et al. [2014] find that accuracy increases by 5.1% for the average analyst who attends meetings. Our results indicate that high *TRUST* and high *DOM* analysts benefit most from these meetings.

The incremental benefit of meetings for the trustworthy- or dominant-looking analysts decays with time. Column 2 results for forecasts issued further into the future in the [181, 360] day window show that the coefficients of $TRUST \times I_{MEET}$ *and* $DOM \times I_{MEET}$ are no longer significant. The insignificant results for a longer window can be viewed as a placebo test that increases confidence for viewing column 1's significant results as real and not from accidental random associations.

These results suggest a possible information access channel for how face impressions contribute to forecast accuracy. The perceptions formed by information possessors from in-person encounters with analysts affect their willingness to share information with the analysts, which would directly affect the analysts' forecast accuracy. In sum, face impressions may be vital to the information acquisition process in capital markets.

3.3 INFORMATION ACCESS CHANNEL: SHOCK FROM REG FD

To investigate further the information access channel for face impression effects, we examine the systematic change to analyst information access to firm insiders from Reg FD. On October 23, 2000, the SEC implemented Reg FD to prevent selective disclosure of private information by public companies. Several studies document that Reg FD leveled the playing field among sell-side analysts by curbing private information flow from managers to analysts (e.g., Cohen, Frazzini, and Malloy [2010], Tang [2013]). We hypothesize that if a particular face factor contributes to better access to private information from company executives, its effect would be weakened post-Reg FD, when the law requires equal access.

We estimate equation (1) for the pre-Reg FD and post-Reg FD period subsamples and present the results in table 4, columns 1 and 2, respectively. The coefficient of *TRUST* is positive and highly significant, at 13.15 pre-Reg FD in column 1 and drops substantially to an insignificant 2.65 (t-statistic = 1.59) post-Reg FD in column 2. In column 3, we estimate a pooled regression for the full period and use an indicator variable $I_{Pre\text{-}FD}$ to denote the difference in the Pre-Reg FD period. The coefficient of $TRUST \times I_{Pre\text{-}FD}$ is positive (6.05%) and significant at the 10% level (two-tailed), consistent with a significant reduction of *TRUST* post-Reg FD. In contrast, *DOM* is 6.43 and highly significant post-Reg FD.[37]

[37] The difference for *DOM* between the two periods is not statistically significant in column 3.

TABLE 4

Face Factors and Forecast Accuracy, the Impact of Reg FD

	(1) Pre-Reg FD Subsample (1990–2000)	(2) Post-Reg FD Subsample (2000–2017)	(3) Full Sample
TRUST	13.150***	2.650	2.650*
	(2.88)	(1.59)	(1.77)
ATTRACT	0.540	−1.770	−2.250
	(−0.00)	(−0.79)	(−0.92)
DOM	4.870	6.430***	6.320***
	(0.62)	(2.82)	(2.83)
$TRUST \times I_{Pre\text{-}FD}$			6.050*
			(1.67)
$ATTRACT \times I_{Pre\text{-}FD}$			−1.970
			(−0.38)
$DOM \times I_{Pre\text{-}FD}$			0.610
			(0.10)
$I_{Pre\text{-}FD}$			−1.680
			(−0.34)
Controls	Yes	Yes	Yes
Adjusted R^2	0.102	0.060	0.063
N	29,163	219,266	248,523

This table presents panel regression results on Regulation FD and the face factor–accuracy relation. The dependent variable *ACCURACY* (in %) is the relative accuracy of an analyst forecast. *TRUST*, *ATTRACT*, and *DOM* correspond to the analyst's face factors of trustworthiness, attractiveness, and dominance, respectively, orthogonalized and scaled to [0, 1] within gender. We include the same set of control variables as in table 2. Columns 1 and 2 correspond to the pre- (1990–2000) and post-Reg FD (2000–2017) periods. Column 3 corresponds to the full sample and includes the interaction variables of each face factor with $I_{Pre\text{-}FD}$, an indicator variable that equals 1 for pre-Reg FD observations. We include a constant and firm fixed effects. We cluster the standard errors by firm and present the *t*-statistics in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

These results are consistent with our hypothesis that trust impressions facilitate private information access to firm insiders and become less crucial post-Reg FD when private communications are no longer permitted. With a level playing field for access to firm insiders, information access to nonfirm sources becomes more beneficial post-Reg FD. This explains why *TRUST* is highly significant pre-Reg FD but not post-Reg FD. In contrast, being perceived as competent may open opportunities for access to information not only from company insiders, but also from nonfirm sources such as industry experts and analyst peers. Therefore, having such alternative sources becomes advantageous post-Reg FD when access to firm information is equalized but is less so pre-Reg FD when the signal from firm insiders is more informative (greater signal-to-noise ratio) relative to signals from alternative sources.

3.4 NEW RELATIONSHIPS AND PERSISTENCE OF FACE FACTOR EFFECTS

In this subsection, we attempt to understand how impression effects evolve over time by examining new versus seasoned social interactions between analysts and information possessors. As explained earlier, psychologists find that novelty from a new face, especially one that is attractive, invites attention, which may increase communication between interacting parties initially, but the novelty wears off eventually. Further, the attractiveness impression reduces the perceived quality of the face possessor (Gheorghiu et al. [2017]) and thus is less likely to be associated with a positive feedback effect. Thus, we hypothesize that an attractive new face has a strong positive effect on information access, but the effect disappears with time.

For the other two face factors, a longer term relationship may have two opposing effects. On the one hand, learning about the analyst can occur over time, so initial misperceptions from a new relationship may be corrected over time. On the other hand, initial impressions, whether correct or not, may trigger self-reinforcing feedback effects so that initial impression effects persist. For example, observers may be more likely to provide information to analysts they perceive as high-*TRUST* or high-*DOM*. The information improves accuracy for these analysts, but the observers may attribute the better accuracy to the higher quality of the analysts, thereby justifying the observers' initial impressions in a positive feedback loop.

Another pathway may be that the perceptions themselves induce behavior by the observed in a manner consistent with observers' perceptions even when inaccurate at the start. This may result in dominant or trustworthy-looking analysts working harder to be more accurate even when they do not have the underlying dominant or trustworthy trait.[38]

We examine two settings for the duration of the relationship between analysts and information possessors. The first is when the analyst is new to an industry, and the second is when the company the analyst follows has recently hired a new CEO or CFO. Specifically, we define $I_{NEW\_ANALYST}$ as 1 if an analyst's industry experience is two years or less, and 0 otherwise, and $I_{NEW\_CEO/CFO}$ as 1 if the forecast was made within two years of a new CEO or CFO hire, and 0 otherwise.[39] We estimate equation (2), replacing the meet indicator variable with the new relationship indicators. The coefficients on the *Face Factors* base variables capture the relation between *Face Factors* and accuracy for seasoned relationships, and the interaction terms with the new-relation indicators capture the marginal effect of *Face Factors* associated with the new relationships.

Table 5 reports the regression results for the new-to-industry setting in column 1 and for the new CEO/CFO setting in column 2. We focus first on the attractiveness factor. The coefficient for $ATTRACT \times I_{NEW\_ANALYST}$ is 8.20 and $ATTRACT \times I_{NEW\_CEO/CFO}$ is 6.15, and both are positive and significant at the 5% level. These results are consistent with past studies' findings of

[38] For example, Zebrowitz, Voinescu, and Collins [1996] find that the perception of an individual's facial honesty during childhood is associated with their actual honesty as an adult.

[39] We identify new CEO/CFO using information obtained from ExecuComp. In our sample, 45.2% of analyst-year (26.5% of forecast) observations belong to a new analyst situation ($I_{NEW ANALYST}$=1), and 20.9% of firm-year (24.5% of forecast) observations are in a new management situation, ($I_{NEW CEO/CFO} = 1$). Our results are robust if we define the new relationship as within the first three years of the analyst's industry experience and within three years of a CEO or CFO change.

TABLE 5
Face Factors and Forecast Accuracy, New Relationships

	(1) $I = I_{NEW\ ANALYST}$	(2) $I = I_{NEW\ CEO/CFO}$
$TRUST \times I$	−3.770	−0.626
	(−1.52)	(−0.26)
$ATTRACT \times I$	8.204**	6.146**
	(2.38)	(2.00)
$DOM \times I$	−4.677	2.565
	(−1.28)	(0.80)
TRUST	4.233**	3.225**
	(2.57)	(2.13)
ATTRACT	−4.040	−3.521
	(−1.49)	(−1.46)
DOM	7.619***	7.655***
	(3.12)	(3.23)
I	−1.072	−4.825
	(−0.33)	(−1.64)
Controls	Yes	Yes
Adjusted R^2	0.064	0.064
N	248,523	248,523

Using panel regressions, this table shows how the relation between analyst face factors and forecast accuracy varies with the length of the analyst's relationship with company management and other capital market participants. The dependent variable *ACCURACY* (in %) is the relative accuracy of an analyst forecast. *TRUST*, *ATTRACT*, and *DOM* correspond to the analyst's face factors of trustworthiness, attractiveness, and dominance, respectively, orthogonalized and scaled to [0, 1] within gender. The indicator variable (*I*) represents the condition of new relationships: $I_{NEW\ ANALYST}$ equals 1 if the forecast was made within two years after an analyst started to follow the industry, and 0 otherwise; $I_{NEW\ CEO/CFO}$ equals 1 if the forecast was made within two years after the firm experienced CEO or CFO turnover, and 0 otherwise. The set of control variables is the same as in table 2. We include a constant, firm fixed effects, and year fixed effects. The *t*-statistics (presented in parentheses) are computed with standard errors clustered by firm.***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

a beauty premium in the labor market (see, e.g., Mobius and Rosenblat [2006], Andreoni and Petrie [2008], Cao et al. [2020]), but only for new faces. The base *ATTRACT* variable is not significant, so there is no beauty premium for seasoned analysts in our sample. The transient nature of the beauty premium is consistent with the novelty hypothesis. The initial beauty premium erodes over time when information possessors get used to the beautiful face, so beauty no longer garners privileged access to information.

In contrast, the coefficients for the base *TRUST* and *DOM* variables are positive and significant, at 4.23 and 7.62 (3.23 and 7.66 in column 2), respectively, confirming the table 2 baseline results that trustworthiness and dominance impressions improve accuracy. The insignificance of the interaction of these factors with the new relationship indicator suggests that the *TRUST* and *DOM* effects persist, consistent with possible self-fulfilling feedback effects for these impressions.

3.5 EX ANTE FIRM UNCERTAINTY AND FACE FACTOR THREAT ASSESSMENTS

We next explore the role of ex ante uncertainty about a firm's fundamentals to gain further insight into the potential role of impressions from social interactions on analysts' information acquisition. Standard Bayesian learning models imply that information is more valuable when investors face higher ex ante uncertainty, all else being equal. As mentioned in section 1, evolutionary theory suggests that being perceived as trustworthy is especially beneficial for survival in high-threat environments (Oosterhof and Todorov [2008]). Highly uncertain environments are akin to high-threat situations, so the impression that a high-*TRUST* analyst is approachable may be an especially beneficial channel through which the analyst can gain access to information.

We use two ex ante uncertainty measures: earnings volatility, defined as the standard deviation of seasonal earnings changes over the prior four years (Thomas [2002], Dichev and Tang [2009]), and analyst forecast dispersion, measured as the standard deviation of analyst forecast errors over the previous two years (Barron et al. [1998], Barron, Byard, and Kim [2002]). We define I_{HIGH_EV} ($I_{HIGH\_DISPERSION}$) as equal to 1 if earnings volatility (analyst forecast dispersion) is greater than the sample median, and 0 otherwise. We estimate panel regressions of *ACCURACY* on *Face Factors* and their interactions with the uncertainty indicator as shown in equation (2) but replace I_{MEET} with $I_{HIGH\ EV}$ or $I_{HIGH\ DISPERSION}$.

Table 6, column 1, reports the regression results for earnings volatility as the uncertainty measure. The key variable of interest is the interaction term *Face Factors* × *I*. Results in column 1 show that the coefficients for the interaction of *TRUST* and $I_{HIGH\_DISPERSION}$ is 6.95 and highly significant. In comparison, the coefficient of *TRUST* is not significant. Similarly, in column 2, which uses analyst earnings volatility as the measure of uncertainty, *TRUST* × I_{HIGH_EV} is 4.37 and significant at the 10% level, whereas *TRUST* is insignificant. In addition, the *DOM* coefficients are positive and significant in both columns, showing that the association between *DOM* and forecast accuracy is present in both low- and high-uncertainty environments.

In sum, the findings suggest that impressions about the analysts' trustworthiness may be especially valuable for their obtaining access to information in high-uncertainty environments, consistent with our conjecture that information possessors feel more comfortable sharing information with analysts they perceive to be more trustworthy in high-threat environments.

4. *Capital Market Outcomes*

Our analysis so far has established a strong association between face-based trait impressions and analyst accuracy. An important next question is whether impressions from social interactions affect information dissemination in capital markets. Gheorghiu et al. [2017] find that the facial appearance of scientists influences how audiences receive their research. The research is rated as higher quality when the researchers appear more competent and moral. Therefore, we examine whether face factors modulate investors' sensitivity to analyst forecast revisions.

TABLE 6

Face Factors and Forecast Accuracy, by Fundamental Uncertainty

	(1) $I = I_{HIGH\_DISPERSION}$	(2) $I = I_{HIGH\_EV}$
$TRUST \times I$	6.953***	4.369*
	(2.91)	(1.76)
$ATTRACT \times I$	1.135	2.517
	(0.36)	(0.73)
$DOM \times I$	−1.463	5.215
	(−0.42)	(1.45)
TRUST	−0.314	0.784
	(−0.16)	(0.37)
ATTRACT	−2.629	−3.443
	(−0.87)	(−1.02)
DOM	7.891***	5.474*
	(2.80)	(1.79)
I	−2.093	−7.414**
	(−0.71)	(−2.44)
Controls	Yes	Yes
Adjusted R^2	0.059	0.063
N	204,160	233,586

This table presents panel regression results on firm's fundamental uncertainty and the face factor–accuracy relation. The dependent variable *ACCURACY* (in %) is the relative accuracy of an analyst forecast. *TRUST*, *ATTRACT*, and *DOM* correspond to the analyst's face factors of trustworthiness, attractiveness, and dominance, respectively, orthogonalized and scaled to [0, 1] within gender. The indicator variable (*I*) represents the condition of higher underlying uncertainty: $I_{HIGH\_DISPERSION}$ equals 1 if analyst forecast dispersion in the past two years is greater than the sample median, and 0 otherwise; I_{HIGH_EV} equals 1 if earnings volatility in the past two years is greater than the sample median, and 0 otherwise. The set of control variables is the same as in table 2. We include a constant, firm fixed effects, and year fixed effects. We cluster the standard errors by firm and present the *t*-statistics in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

4.1 PRICE REACTIONS TO FORECAST REVISIONS: BASELINE RESULTS

Following Gleason and Lee [2003], Jiang et al. [2016], and Jung et al. [2019], we calculate the three-day cumulative abnormal return $CAR[-1, +1]$ as the difference between the buy-and-hold stock return and the CRSP value-weighted index return around the forecast release day.[40] We estimate the following panel regression model:

$$CAR_{i,j,t} = \beta_0 + \beta_1 REVISION_{i,j,t} + \beta_2 Face\ Factors_i \times REVISION_{i,j,t} + \delta X + \gamma X \times REVISION_{i,j,t} + \varepsilon_{i,j,t}, \quad (3)$$

[40] We obtain forecast dates from the I/B/E/S historical detail file. Following previous studies (Gleason and Lee [2003]; Jiang et al. [2016]; Jung et al. [2019]; Hirshleifer et al. [2019]), we use the three-day abnormal returns around the forecast. Day –1 to capture potential price changes from "analyst tipping" to preferred institutional investors ahead of the public release of the analysts' forecasts (Irvine, Lipson, and Puckett, [2007]; Markov, Muslu, and Subasi [2017]). Day +1 is included to capture market reactions to after-hours forecasts. Table A6 shows that results are robust to alternative CAR windows of CAR[–1, 0] and CAR[0, 0].

where *REVISION* is the change in an analyst's forecast from the analyst's prior forecast, scaled by the stock price two trading days prior.[41] We include the following controls and their interactions with *REVISION*: analyst and brokerage house characteristics measured over the prior year as in equation (1), and, following Clement and Tse [2003], a measure of analyst skill, *LAG_ACCURACY*, defined as the analyst's average forecast accuracy for the firm over the prior eight quarters. The inclusion of *LAG_ACCURACY* accounts for both the direct effect of analyst skill and the indirect effect of face factors on returns working through the factors' effect on skill.[42]

Table 7 reports the results, with *t*-statistics computed with standard errors clustered by firm in parentheses. We include quarter fixed effects and the Fama–French 17 industry fixed effects in all columns. In column 1, we include all control variables and their interactions with *REVISION*. In column 2, we follow Guest [2021] and Gipper, Leuz, and Maffett [2020] and include additional interactions of fixed-effects indicators with *REVISION*. The key variables of interest are *REVISION* × *Face Factors*, which captures the modulating role of face factors on price responsiveness, incremental to the effect of other variables, including measurable skills.

Both columns show that the coefficients on *REVISION* × *TRUST* are positive and significant, at 0.334 and 0.369, respectively, indicating that investors are incrementally more sensitive to revisions issued by analysts who appear more trustworthy, even after controlling for analysts' other characteristics such as past forecast accuracy. In addition, the coefficient estimates are similar with or without the interactive fixed effects, suggesting that the results are less likely to be attributable to omitted variables that are industry-related or specific to a particular time period.[43]

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[41] Following Clement, Frankel, and Miller [2003], we exclude days with multiple forecasts or days with earnings announcements to remove potential confounding events on stock returns. Following the prior literature, forecast revisions are changes from the analyst's prior forecast (Gleason and Lee [2003], Bonner, Hugon, and Walther [2007], Jung et al. [2019]).

[42] 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 *FACE FACTORS* × *REVISION*.

[43] The coefficient on *REVISION* × *DOM* is insignificant, suggesting that dominant analysts (who have greater accuracy) do not generate significant higher return reactions to their forecasts. To explore a potential explanation, we consider the timeliness of the forecasts. Prior literature has shown that market reactions are stronger for more timely forecasts (Cooper, Day, and Lewis [2001]; Shroff, Venkataraman, and Xin [2014]). We examine the difference in forecast horizon between *TRUST* and *DOM* analysts, where horizon is the number of days between the forecast date and the corresponding fiscal quarter end. We find that High-*DOM* analysts' forecasts are, on average, 4.6 days *later* than that of the high-*TRUST* forecast. (The spreads in forecast horizon between High- and Low-*DOM* and between High- and Low-*TRUST* are comparable.) All else being equal, the earlier announcements of high-*TRUST* forecasts trigger a stronger market reaction.

TABLE 7
Face Factors and Market Reactions to Analyst Forecasts

	(1)		(2)		(3)	
REVISION	0.932**	(1.96)				
REVISION × *TRUST*	0.334*	(1.84)	0.369**	(1.99)	0.179	(0.78)
REVISION × *ATTRACT*	−0.037	(−0.15)	0.039	(0.16)	0.072	(0.25)
REVISION × *DOM*	0.071	(0.28)	−0.013	(−0.05)	−0.001	(−0.04)
REVISION × *TRUST* × I_{HIGH_INST}					0.594*	(1.69)
REVISION × *ATTRACT* × I_{HIGH_INST}					−0.048	(−0.10)
REVISION × *DOM* × I_{HIGH_INST}					−0.075	(−0.16)
REVISION × I_{HIGH_INST}					−0.407	(−1.09)
REVISION × *LAG_ACCURACY*	0.534*	(1.81)	0.489*	(1.71)	0.511*	(1.74)
REVISION × *fWHR*	0.322*	(1.81)	0.332*	(1.89)	0.476*	(1.68)
Other firm/analyst/forecast characteristics controls	Yes		Yes		Yes	
REVISION × Controls	Yes		Yes		Yes	
Revision × Fixed effects	No		Yes		Yes	
Adjusted R^2	0.013		0.018		0.018	
N	85,643		85,643		85,643	

This table shows panel regression results on the relation between analyst face factors and market reactions to analyst earnings forecast revisions. The dependent variable is the three-day cumulative abnormal return, *CAR*[*−1, +1*], calculated as the difference between the individual stock return and the CRSP value-weighted index return. *TRUST*, *ATTRACT*, and *DOM* correspond to the analyst's face factors of trustworthiness, attractiveness, and dominance, respectively, orthogonalized and scaled to [0, +1] within gender. *fWHR* is the analyst's facial width-to-height ratio. *LAG_ACCURACY* is the mean relative accuracy of the analyst's forecast over the last eight quarters. *REVISION* is the difference between the analyst's current and preceding earnings forecast for a firm-quarter, scaled by the stock price two trading days prior to the current forecast date. I_{HIGH_INST} is an indicator variable that equals 1 if a firm's institutional ownership is in the top quartile for the prior industry-year. We include the following control variables: forecast horizon (*HORIZON*), the female indicator (I_{FEMALE}), analyst general and firm-specific experience (*GEXP* and *FEXP*), age (*AGE*), number of firms the analyst follows (*PORFOLIO_SIZE*), size of the brokerage house that the analyst is affiliated with (*BROKER_SIZE*), lagged firm characteristics (return on asset *ROA*, debt-to-equity ratio *LEVERAGE*, logarithm market capitalization *SIZE*, book-to-market ratio *BM*, one-week buy-and-hold abnormal return *BHAR*). All regressions include a constant, industry fixed effects, and quarter fixed effects. The *t*-statistics are computed with standard errors clustered by firm and reported in parentheses.***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

To interpret the economic magnitude of the incremental effect, we consider column 1.[44] A one-standard-deviation increase in *TRUST* translates into a 6.23% (= 0.334 × 0.174/0.932) increase in the return–revision relation relative to the baseline effect of 0.932. The economic magnitude of the change in the return–revision relation by *TRUST* is comparable to that of other well-documented analyst characteristics.[45]

These results show that the stock market reacts more strongly to earnings forecasts issued by the more trustworthy-looking analysts. A natural question is what drives such strong reactions. Similar to tests in section 3 where

[44] Column 2 includes the interaction effects of fixed effects indicators, which complicate the interpretation of the coefficient of base *REVISION*.

[45] These other characteristics include industry-related experience (6.88%–10.59%), from Bradley et al. [2017, table 4] and past forecast accuracy as in Clement [1999] (6.55%, computed using our estimated coefficients as 0.534 × 0.1143/0.932).

we show face impression associations with accuracy are strengthened after recent in-person meetings between analysts and information possessors, we consider next how face impressions alter investor reactions to forecast revisions for high institutional ownership firms when investors are more likely to have met the analyst.

4.2 PRICE REACTIONS TO FORECAST REVISIONS: INSTITUTIONAL OWNERSHIP

The literature suggests that institutional investors are more likely to have had face-to-face interactions with analysts than retail investors and to have seen the analysts' pictures when included in their reports. Kirk and Markov [2016] suggest that institutional investors actively participate in analyst/investor activities and communicate with both company managers and analysts at these events. Thus, we expect that the relations between face factors and market reactions to forecast revisions are more pronounced in firms with high institutional ownership.[46]

Using data from the 13F database of Thomson Reuters, we measure institutional ownership at the end of each year and define $I_{HIGH\ INST}$ as equal to 1 for firms in the top institutional ownership quartile of the Fama–French 17 industry classification for that year. In equation (3), we add the interaction of *Face Factors* $\times$ *REVISION* with $I_{HIGH\ INST}$; where the triple-interaction terms are the key variables of interest in the regression.

Table 7, column 3, presents the results. The coefficient of *REVISION* $\times$ *TRUST* $\times$ $I_{HIGH\ INST}$ is positive and significant, suggesting that, for stocks with high institutional ownership, the effect of *TRUST* on the return–revision relation is a hefty 77.8% (= 0.594/0.334 – 1), which is higher than the *TRUST* effect for stocks with average institutional ownership in column 1. None of the coefficients for the face factor base variables are significant, so face factor associations with return sensitivity to forecast revisions are absent for low institutional ownership firms. Such results are less likely to be driven by innate traits and are more suggestive of perception effects from the social interaction channel.[47]

Collectively, the result suggests that all else being equal, return responsiveness to the forecast revisions of analysts who look trustworthy are substantially higher for firms with many institutional owners who are more likely to have had in-person social interactions with the analysts than retail investors and who are more likely to be influenced by the face of analysts. In sum, face impressions of analysts have important implications for

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[46] In limited attention theory models (e.g., Hirshleifer and Teoh [2003]), price is a weighted average of investor beliefs, so any potential trader can affect price.

[47] We thank an anonymous referee for this suggestion.

information dissemination in capital markets when major shareholders have seen the analysts' faces.

5. *Gender Effects and Labor Market Outcomes*

The social psychology literature finds that impressions from faces vary significantly with the gender of the observed and with societal norms (Sutherland et al. [2015], Oh et al. [2019, 2020]). A growing body of economics literature also suggests strong evidence of gender stereotypes and discrimination in hiring, compensation, and career dynamics (footnote 8). Therefore, we study the role of gender in face impression associations with accuracy and with analyst career prospects.

5.1 THE ROLE OF GENDER IN FACE FACTORS AND THE FORECAST ACCURACY RELATIONSHIP

Evidence in psychology literature suggests that gender stereotypes create normative standards for behavior that induce rewards when the stereotypes are confirmed and penalties when the stereotypes are violated (Heilman [2012]). Oh et al. [2019, 2020] find that gender stereotypes exist in impressions about dominance and trustworthiness. Women specifically are judged negatively to the extent that their looks do not conform to societal stereotypes for the different sexes.

Males are stereotyped as being more aggressive (one key component of the dominance trait), whereas females are perceived as more nurturing. Vernon et al. [2014] note that *DOM* loads heavily on maleness traits. Therefore, males with high *DOM* scores conform to societal stereotypes and confer benefits for males, whereas high *DOM* violates the female stereotype and therefore is injurious to females. Although attractiveness fits the general stereotype that women are more attractive than men, the Gheorghiu et al. [2017] finding that attractiveness is perceived as low quality in the scientific arena suggests that attractive female analysts may be disadvantaged.

To investigate whether these gender impression effects from the psychology and labor economics literature have similar effects in the analyst arena, we estimate equation (1) again just for the female-only sample, dropping the female indicator. Table 8 present the results. The coefficients of *ATTRACT* and *DOM* are indeed negative and significant, whereas *TRUST* is insignificant. This pattern is in sharp contrast to the significantly *positive* relations of *TRUST* and *DOM* for accuracy that is presented in table 2 for the full sample, which is dominated by male analysts (87.3% of the observations).

These results corroborate the inference of the presence of gender discrimination revealed in the psychology and labor economics literature. Female analysts who are perceived to be dominant tend to be judged negatively, so the information possessors may be less willing to share

TABLE 8
Face Factors and Forecast Accuracy: Female Subsample

TRUST	2.741
	(1.16)
ATTRACT	−9.198***
	(−3.03)
DOM	−8.550**
	(−2.17)
fWHR	−3.653
	(−1.12)
Controls	Yes
Adjusted R^2	0.068
N	29,333

This table shows the relation of analyst face factors and forecast accuracy for the female sample. The dependent variable *ACCURACY* (in %) is the relative accuracy of an analyst forecast. *TRUST*, *ATTRACT*, and *DOM* correspond to the analyst's face factors of trustworthiness, attractiveness, and dominance, respectively, orthogonalized and scaled to [0, 1] within gender. We include the same set of control variables as in table 2. We include a constant, industry fixed effects, and year fixed effects. We cluster the standard errors by firm, and present the *t*-statistics in parentheses.***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

information with these analysts. As for attractive female analysts, they may be perceived as being low quality, which would also discourage information possessors from sharing information with them.[48]

5.2 FACE FACTORS AND ALL-STAR SELECTION OUTCOMES

We turn next to the role of gender for face factor effects on the analyst labor market. We measure an analyst's career advancement using the All-Star status, as determined by *Institutional Investor* magazine's annual survey of asset managers and buy-side analysts. Being selected as an All-Star Analyst indicates a successful career for the sell-side analyst as it brings significant increases in prestige, clients, and compensation (Groysberg, Healy, and Maber [2011]).

We investigate whether an analyst's trait impressions affect the analyst's probability of obtaining All-Star status (I_{STAR}). We estimate the following analyst-year logit regression for the male and the female samples separately:[49]

$$I_{STAR,\ i,t} = \beta_0 + \beta_1 Face\ Factors_i + \beta_2 X + \varepsilon_{i,t}. \tag{4}$$

[48] An interesting topic for further study is gender differences in how perceptions from face factors operate. Li et al. [2020] find a cultural difference in the effect of beauty; there is a beauty premium on analysts' All-Star ranking in China, but a beauty penalty for U.S. analysts. Bohren, Imas, and Rosenberg [2019] find that experience reverses discrimination effects. We find that the *ATTRACT* and *DOM* penalties are present for analysts with low past accuracy only. The direction of effect is consistent but weaker than the reversal effect of Bohren et al.

[49] The set X of control variables follows from Bradley et al. [2017] and is measured for the prior year, which includes: the analyst's All-Star status (*LAG_STAR*), analyst age (*AGE*), analyst mean forecast accuracy (*MEAN_ACCURACY*), the number and total market value of

TABLE 9
Face Factors and All-Star Analyst Selection Outcomes

	(1) Female	(2) Male	(3) Test of Coefficients Equality
TRUST	−0.353	0.341	−0.694
	(−0.47)	(0.71)	($p = 0.436$)
ATTRACT	1.851	−0.767	2.617*
	(1.41)	(−1.39)	($p = 0.066$)
DOM	−4.363***	1.629**	−5.991***
	(−3.35)	(2.20)	($p = 0.000$)
fWHR	1.668	−0.414	
	(1.34)	(−0.89)	
LAG_STAR	4.027***	3.733***	
	(8.06)	(18.22)	
PORTFOLIO_SIZE	−0.047**	0.018***	
	(−2.10)	(2.65)	
SIC2	0.1874	0.033	
	(1.52)	(0.76)	
BROKER_SIZE	0.0362**	0.046***	
	(2.23)	(5.87)	
MEAN_ACCURACY	0.654	1.121***	
	(1.02)	(3.11)	
PORTFOLIO_CAP	0.023	0.024***	
	(1.16)	(2.79)	
AGE	0.093***	−0.020**	
	(3.30)	(−2.29)	
Pseudo R^2	0.470	0.501	
N	687	5,030	

This table reports the Logit regressions of analyst face factors on All-Star selection outcomes. Columns 1 and 2 correspond to the female and male analyst subsamples, respectively. The dependent variable I_{STAR} is the All-Star status indicator. *TRUST*, *ATTRACT*, and *DOM* correspond to the analyst's face factors of trustworthiness, attractiveness, and dominance, respectively, orthogonalized and scaled to [0, 1] within gender. *fWHR* is the analyst's facial width-to-height ratio. *AGE* is the age of the analyst. We include the following controls, measured for the prior year: the analyst All-Star status (*LAG_STAR*), the analyst's mean forecast accuracy (*MEAN_ACCURACY*), the number and total market capitalization of firms and two-digit SICs of the firms the analyst follows (*PORTFOLIO_SIZE*, *PORTFOLIO_CAP*, and *SIC2*), and the size of the brokerage house that the analyst is affiliated with (*BROKER_SIZE*). We report the chi-square tests (Wald) and the corresponding p-values for testing the equality of coefficients for female and male in column 3. All estimations include an intercept and year fixed effects. Z-statistics are presented in parentheses.***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 9 shows that the coefficient of *DOM* is negative and significant for female analysts but positive and significant for male analysts. In terms of economic magnitude, holding all other variables at the mean, a female analyst with the highest *DOM* score is 8.4% less likely to obtain All-Star status than one with the lowest *DOM* score, a whopping 67.7% reduction from the unconditional probability of 12.4% for all female analysts. In contrast,

firms (*PORTFOLIO_SIZE*, *PORTFOLIO_CAP*), the number of industries covered by the analyst (*SIC2*), and the size of the analyst's brokerage house (*BROKER_SIZE*). We also include year fixed effects. The results, not tabulated for brevity, show robustness to including the quadratic control for *MEAN ACCURACY*.

the highest *DOM* male analyst is 1.8% more likely to be an All-Star than the lowest *DOM* male analyst, which is a 25.4% increase from the unconditional probability of 7.1% for male analysts. The test in column 3 suggests the coefficients of *DOM* are statistically different across female and male analysts.[50]

Our control variables are likely to soak up a significant portion of the differential ability effects on the likelihood of All-Star selection. It strikes us as unlikely that the opposite signs of the coefficient between the gender subsamples can be explained by *DOM*'s being a positive ability indicator for male analysts and a negative ability indicator for female analysts. It seems more likely that the gender differences for All-Star status are associated with face impression effects. Our evidence is consistent with the literature mentioned at the beginning of section 5 that finds women are likely to be punished when their appearance does not conform to gender stereotypes. What is more striking in our setting is that gender bias exists even in a profession where performance can be relatively objectively measured. Although these are strong results, we caution that a more definitive inference about the existence of gender discrimination would require further exploration to rule out alternative explanations.[51]

6. *Robustness Analyses and Measurement Errors*

Our tests control for a rich set of firm, analyst, and brokerage-level characteristics, including firm and year fixed effects, to alleviate potential endogeneity concerns. In this section, we provide robustness checks with alternative measures of key variables and additional fixed effects. We also consider potential mismeasurement of face factors due to stale photos, nonrandom selection of LinkedIn photos, or the ML algorithm we use.

6.1 ROBUSTNESS CHECKS

Alternative face factors: As mentioned previously, we follow Vernon et al. [2014] and use orthogonalized face factors to reduce potential multicollinearity in the regressions that jointly include the face factors. Table A4 reports that results are robust to nonorthogonalized face factors in column 1, orthogonalized face factors following the *ATTRACT–TRUST–DOM order* in column 2, and orthogonalized face factors following the *DOM–TRUST–ATTRACT* order for the accuracy test (panel A), the market reaction test (panel B), and the All-Star test (panel C).

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[50] For the control variables, we find that female analyst All-Star probability increases with past All-Star status and the size of the employer's brokerage house but decreases with the number of firms they follow. For male analysts, All-Star probability increases with prior All-Star status, the size of the employer brokerage house, the number and value of the firms they follow, and their forecast accuracy.

[51] For example, *DOM* female analysts may prefer or receive firm assignments in industries with lower potential for attaining All Star status because of an accident of history, societal gender norms, or work–life balance considerations.

Age fixed effects: Face impressions may be age-dependent in a nonlinear manner that is not fully captured by *AGE* in the regressions. We include age fixed effects in column 4 to the same robustness regressions in table A4, panels A–C, as above. The results for these regressions are very similar to those presented in tables 2, 7, and 9.

Error clustering method: In the main tests, we cluster standard errors by firm to account for potential correlations among the standard errors at the firm level. In table A4, column 5, we cluster standard errors by analyst, and in column 6, we use two-way clustered standard errors by firm and by year, and the results are qualitatively similar.

Alternative forecast accuracy measures: Our results are robust to using an alternative measure of forecast accuracy, *AFE*, which is estimated as the absolute value of the difference between the forecast and actual EPS (e.g., He et al. [2019], Li et al. [2020]). We define *ACCURACY_AFE* as the negative of *AFE* and redo the table 2, column 4, regression.[52] Table A4, panel A, column 7, shows that the economic magnitudes of the coefficient estimates are similar to our main result in table 2: an increase in *TRUST*(*DOM*) from 0 to 1 is associated with a 4.24% (6.67%) increase in *ACCURACY_AFE* relative to its mean of 7.81%.

6.2 MEASUREMENT ERRORS IN FACE FACTORS

In this subsection, we address potential concerns that the LinkedIn profile pictures may not reflect analysts' appearance to observers in actual in-person meetings because the photos may have been edited, may be unrepresentative of their actual appearance, or are stale in the sense that the analyst may have aged since the photograph was taken.

Representativeness of the photographs: As LinkedIn profile pictures are self-posted, one concern is that they may not represent what the analysts normally look like. However, given that the LinkedIn platform is for *professional* networking, the profile picture is more likely to represent one's image in professional settings.[53] Furthermore, as we explain in subsection 2.1 and figure 1, we preprocess the photos to standardize photo size, orientation, and face position to increase ambiance homogeneity, so these sources of measurement error in the face factors are reduced.

Nevertheless, we check for representativeness by obtaining photos of our sample's analysts from their employer websites (if available). As these are official business headshot portraits, we gain uniformity of professional

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[52] To be consistent with the calculation of the dependent variable, we follow the literature and include the same list of control variables as in the raw value instead of the demeaned value used in table 2.

[53] LinkedIn.com recommends that users post a recent photo that closely resembles themselves and has explicit suggestions for preparing profile pictures, such as using a high-resolution image, choosing the right expression to express themselves in a professional setting, and taking the photo in soft, natural light. For more details, see https://business.linkedin.com/talent-solutions/blog/2014/12/5-tips-for-picking-the-right-linkedin-profile-picture.

lighting and ambiance and reduce the likelihood of self-selection and self-editing. We found official company photos for 134 analysts, and these *Face Factors* are highly correlated with those from the LinkedIn profile pictures, with correlation coefficients of 66.62% for *TRUST*, 64.49% for *ATTRACT*, and 66.72% for *DOM*. Thus, there is some assurance that the LinkedIn pictures are likely to be representative.

Re-touched photographs: LinkedIn profile photos, if touched-up, may lead to faulty *Face Factor* scores that do not capture impressions about the analysts from observing their faces in real life. We follow Wang et al. [2019] to identify re-touched photos to address this concern.[54] Specifically, we analyze each image with a deep learning model to estimate the probability that the input image has been edited; we find that the mean editing probability for pictures in our sample is low, at less than 1% (mean = 0.8%, median = 0). We identified 12 analyst photos with an editing probability of greater than or equal to 10% and removed these observations from our analysis.

Panel A, column 1, panel B, column 1, and panel C of table A5, A6 present the results on forecast accuracy, return reactions, and career outcomes, respectively. The results are robust, so edited profile pictures are unlikely to drive our findings.

Stale photos and aging: Face impressions can change with the age of the observed, which may raise two issues in our tests. First, the LinkedIn photo we downloaded in 2018 may correspond to a younger version of the analyst. To estimate the extent of photo staleness, we use the Face++ app to estimate AGE_{photo} for the approximate age of the analyst when the photo was taken, and we compare it with estimated *AGE* in 2018 using college start year provided in the LinkedIn profile. We find that the median (mean) age difference, $AGE_{photo} - AGE$, is 0 (0.39), and the standard deviation is 8.5. The age difference is less than six years for more than 50% of the analysts. Furthermore, for 73.9% of our forecast sample, the age range (as of 2018) is between 30 and 50, when aging tends to be slower and less visible. These findings reduce the concern about stale photos in our sample.

The second issue is that the LinkedIn profile pictures that we obtained in 2018 may not reflect an analyst's appearance at the time the dependent variables were considered. We conduct a robustness check by limiting the sample to more recent periods, 2007–2017, when the 2018 pictures may be more representative of the analysts' appearances at the time of their forecasts. Table A5, column 2, reports the results and shows that our main findings are robust.

Errors in variable: The ML algorithm may introduce errors in the extracted *Face Factors* relative to the actual human impressions, which tends to attenuate their estimated coefficients toward 0. The correlation between *Face Factors* and our MTurk human rater scores are 0.92, 0.75, and 0.72 for

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

TRUST, *ATTRACT*, and *DOM*, respectively, suggesting the likelihood of mismeasurement is largest for *DOM*, followed by *ATTRACT* and then *TRUST*.

Despite being the most likely to be mismeasured among the three face variables, *DOM* is highly significant for analyst forecast accuracy (table 2) and for All-Star probability (table 9). Thus, the true *DOM* effects are likely larger, and its mismeasurement does not seem to be a major cause for concern. Moreover, we do find significance for *ATTRACT* in subsamples—for new relationships (new analyst or new CEO/CFO) in table 5. These transient effects of *ATTRACT* match intuition and are harder to explain as measurement error effects.[55]

7. *Concluding Remarks*

Evidence from psychology indicates that people form snap impressions about the personality traits of people they observe from even a fleeting glance at their faces, and these impressions, despite questionable validity, predict many important outcomes (Todorov [2017]). We employ facial recognition and ML techniques to extract impression factors about three traits—trustworthiness, dominance, and attractiveness—from U.S. sell-side analyst photos. We test whether these face impression factors are associated with analyst performance and their capital and labor market outcomes.

We find that the more trustworthy-looking and dominant-appearing analysts produce earnings forecasts that are more accurate, especially after recent in-person meetings between the analyst and firm managers. Investors also respond more strongly to the forecast revisions issued by high-*TRUST* analysts, with an effect that is more pronounced for stocks with high institutional ownership. In contrast, the effect of the attractiveness impression is transient—the impression improves accuracy only in relatively new relationships between analysts and information providers and is not significant for established relationships. Furthermore, while high *DOM* helps male analysts' chances of attaining All-Star status, it substantially reduces female analysts' forecast accuracy and their likelihood of attaining All-Star status.

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[55] We further calibrate the effects of measurement errors in our face factors following a standard modeling setup as follows (see, e.g., Greene [2012]). We assume that the human rater scores represent true face factors (f^*) and the face factors are measured with noise, $f = f^* + u$ with $u \sim N[0, \sigma_u^2]$. Suppose the true relation between f^* and outcome variable y is: $y = \beta f^* + \varepsilon$ with $\varepsilon \sim N[0, \sigma_\varepsilon^2]$. Then, the relation between β, the true regression coefficient, and b, the estimated regression coefficient, is $\beta = b(1 + \frac{\sigma_u^2}{\sigma_{f^*}^2})$. The noise to signal ratio, $\frac{\sigma_u^2}{\sigma_{f^*}^2} = \frac{1}{\rho} - 1$, can be estimated from the correlation between our face factors and human rater scores, $\rho = \mathrm{corr}(f, f^*)$. Hence, we have $\beta = b\frac{1}{\rho}$. Using the estimated coefficients, b, in table 2, column 4, the true coefficients, β, corrected for mismeasurement errors, are 3.40, 2.65, and 9.17 for *TRUST, ATTRACT*, and *DOM*, respectively, and are qualitatively similar to the coefficients reported in table 2, column 4. The calibration exercise further confirms that our findings are robust.

Our findings are consistent with the hypothesis that analysts' trustworthy and dominant appearance grants them privileged access to information, an effect that is sustained via the self-fulfilling prophecy effects of impressions. Our findings are also consistent with the hypothesis that impression effects influence the credibility of the analysts with investors. In addition, our results speak to the role of regulation on disclosure policy on face impression effects by showing that the *TRUST*-accuracy relation is attenuated post-Reg FD. In sum, face impressions from social interactions have important consequences for information acquisition and information dissemination in the capital markets.

Finally, we mention two caveats. We designed our face factors to capture impression effects, and they do not provide direct evidence about the effects of underlying analyst traits. The self-fulfilling prophecy feedback effects make it challenging to sharply disentangle the effects of impressions from underlying analyst traits, and further study is merited. Nevertheless, the stronger results after in-person meetings, the transient effect of *ATTRACT*, the weakening role of *TRUST* post-Reg FD, and gender differences in *DOM* suggest that the underlying traits-based mechanism is less likely to be the main driver of our findings. Second, while we provide striking evidence of poorer outcomes for female analysts with some types of face impressions and in certain situations, further exploration of alternative explanations is also needed before drawing definitive inferences about gender discrimination.

APPENDIX

TABLE A1

Variable Definitions

Variable	Definition
PMAFE	The proportional mean absolute forecast error, calculated as an analyst's absolute forecast error (*AFE*) for a firm j minus *MAFE*, the same-quarter mean absolute forecast error for the firm by analysts in IBES, divided by *MAFE*
ACCURACY	Forecast accuracy, defined as the negative of *PMAFE*
TRUST	An analyst's trustworthiness score, scaled to [0, 1] within gender
ATTRACT	An analyst's attractiveness score, scaled to [0, 1] within gender
DOM	An analyst's dominance score, scaled to [0, 1] within gender
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), scaled to [0, 1] within gender

(*Continued*)

TABLE A1—*(Continued)*

Variable	Definition
I_{FEMALE}	An indicator variable that equals 1 if an analyst is female, and 0 if male
$I_{HIGH\ EV}$	An indicator variable that equals 1 if earnings volatility in the past two years is greater than the sample median, and 0 otherwise
$I_{HIGH\ DISPERSION}$	An indicator variable that equals 1 if analyst EPS forecast dispersion in the past two years is greater than the sample median, and 0 otherwise
$I_{NEW\ ANALYST}$	An indicator variable that equals 1 if the forecast was made within two years after an analyst started to follow the industry (SIC2), and 0 otherwise
$I_{NEW\ CEO/CFO}$	An indicator variable that equals 1 if the forecast was made within two years after the firm experienced CEO or CFO turnover, and 0 otherwise
I_{MEET}	An indicator variable that equals 1 if the forecast is issued within 180 or 360 days following an investor/analyst day event or investor conference in which the analyst and the corporate managers co-participated, and 0 otherwise
I_{HIGH_INST}	An indicator variable that equals 1 if a firm's institutional ownership from aggregated 13-F filings is in the top quartile of industry-year at the prior year-end
ANALYST_FOLLOWING	The number of analysts following a firm that issued at least one EPS forecast in I/B/E/S for a given quarter
DTOP10	An indicator variable that equals 1 if the brokerage house belongs to the top decile size group, minus the corresponding firm-quarter mean of brokerage houses
DSIC2	The number of two-digit SICs an analyst follows, minus the corresponding firm-quarter mean of I/B/E/S analysts
DGEXP	Number of years an analyst existed in I/B/E/S, minus the corresponding firm-quarter mean of I/B/E/S analysts
DFEXP	The number of years an analyst has covered a firm, minus the corresponding firm-quarter mean of I/B/E/S analysts
DHORIZON	The number of days between the forecast date and the earnings announcement date, minus the corresponding firm-quarter mean of I/B/E/S analysts
DAGE	The age of an analyst, minus the corresponding industry-quarter mean of I/B/E/S analysts
DPORTFOLIO_SIZE	The number of firms in an analyst's portfolio minus the corresponding firm-quarter mean of I/B/E/S analysts
SIZE	The natural log of the sum 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

(*Continued*)

TABLE A1—*(Continued)*

Variable	Definition
ROA	Return-on-asset ratio of a firm, calculated as the income before interest and tax (EBIT) divided by lagged total assets
LEVERAGE	Debt-to-equity ratio of a firm, calculated as the total equity divided by total assets
LAG ACCURACY	An analyst's average *ACCURARY* for a given firm over the last eight quarters
RET_{6M}	Cumulative stock return of a firm in the prior six-month period, adjusted by the CRSP value-weighted index
REVISION	The difference between an analyst's current and preceding earnings forecast for a firm-quarter, scaled by the stock price two trading days prior to the current forecast date
HORIZON	The number of days between the forecast date and the earnings announcement date
I_{STAR}	Indicator variable that equals 1 if the analyst is named to *Institutional Investor*'s All-Star team, and 0 otherwise
LAG_STAR	An analyst's prior year I_{STAR} status
MEAN_ACCURACY	An analyst's average *ACCURACY* across all firms that the analyst covers, for a given year
PORTFOLIO_SIZE	The number of firms for which an analyst issued at least one EPS forecast for a given year
PORTFOLIO_CAP	The total market values of the firms an analyst covers for a given year
BROKER_SIZE	The number of analysts a brokerage house employs for a given year
CAR[−1, +1]	The three-day stock return around an analyst's earnings forecast revision date minus the corresponding CRSP value-weighted index return

TABLE A2

Additional Summary Statistics

Panel A: Summary statistics by gender

	Male		Female		
Variables	Mean	SD	Mean	SD	Diff. (Male – Female)
ACCURACY	2.056	71.379	5.007	69.930	-2.951^{***}
TRUST	0.584	0.167	0.589	0.221	-0.005^{***}
ATTRACT	0.519	0.127	0.520	0.171	−0.001
DOM	0.600	0.111	0.588	0.167	0.012^{***}
fWHR	2.160	0.185	2.138	0.182	0.022^{***}
I_{STAR}	0.071	0.256	0.124	0.329	-0.053^{***}
DAGE	0.025	6.190	−0.182	5.668	0.207^{***}
DGEXP	0.215	5.090	0.195	4.645	0.020
DFEXP	0.019	2.942	−0.028	2.720	0.047^{***}
DSIC2	0.030	1.501	−0.070	1.518	0.099^{***}
DPORTFOLIO_SIZE	0.432	6.382	−0.698	4.916	1.130^{***}
DTOP10	0.036	0.447	0.035	0.451	0.001
SIZE	14.745	1.657	14.756	1.646	−0.011
BM	0.534	0.940	0.499	0.901	0.035^{***}

(*Continued*)

TABLE A2—*(Continued)*

Panel B: Pearson correlations

	ACURACY	*TRUST*	*ATTRACT*	*DOM*	I_{FEMALE}	*BROKER SIZE*	*ANALYST FOLLOW*	*DSIC2*
TRUST	0.004**							
ATTRACT	−0.002	0.022**						
DOM	0.013**	−0.054**	−0.517**					
I_{FEMALE}	0.013**	0.009**	0.002	−0.031**				
BROKER_SIZE	−0.003	0.023**	0.021**	0.032**	0.021**			
ANALYST_FOLLOWING	0.008**	−0.020**	0.045**	0.039**	0.036**	0.039**		
DSIC2	−0.015**	0.002	0.030**	−0.051**	−0.021**	−0.039**	0.010**	
DTOP10	0.002	0.013**	0.062**	0.002	−0.001	0.586**	0.011**	−0.028**
DGEXP	0.003	−0.039**	−0.158**	0.081**	−0.001	0.005**	−0.020**	0.065**
DFEXP	0.015**	−0.009**	−0.049**	0.022**	−0.005**	−0.002	−0.007**	0.033**
DAGE	−0.002	−0.015**	−0.046**	0.092**	−0.011**	0.000	0.000	0.046**
DHORIZON	−0.232**	0.011**	−0.014**	−0.008**	−0.002	−0.019**	−0.007**	0.006**
DPORFOLIO	0.003	−0.034**	0.030**	−0.056**	−0.058**	0.068**	0.017**	0.503**
SIZE	−0.003	−0.026**	0.037**	0.031**	0.002	0.157**	0.676**	−0.013**
BM	0.001	−0.018**	−0.010**	0.011**	−0.012**	−0.003	−0.097**	0.015**
RET_{6M}	−0.008**	0.004	0.000	0.002	−0.009**	−0.015**	−0.030**	−0.002

(Continued)

TABLE A2—*(Continued)*

	DTOP10	*DGEXP*	*DFEXP*	*DAGE*	*DHORIZON*	*DPORTFOLIO*	*SIZE*	*BM*
DGEXP	-0.006^{**}							
DFEXP	-0.001	0.481^{**}						
DAGE	-0.013^{**}	0.254^{**}	0.186^{**}					
DHORIZON	-0.015^{**}	-0.007^{**}	-0.019^{**}	-0.016^{**}				
DPORFOLIO	0.125^{**}	0.223^{**}	0.125^{**}	0.053^{**}	-0.033^{**}			
SIZE	0.006^{**}	-0.013^{**}	-0.010^{**}	0.000	0.002	-0.004^{**}		
BM	0.005^{**}	0.026^{**}	0.016^{**}	0.000	0.000	0.026^{**}	-0.192^{**}	
RET_{6M}	-0.004	-0.001	0.000	-0.002	0.001	0.001	0.077^{**}	-0.131^{**}

This table provides additional summary statistics. Panel A reports the distributional statistics by gender and tests the differences in means with grouped *t*-tests. The variables are at the forecast-level, except for, I_{STAR}, which is at the analyst-year level. Panel B reports correlation coefficients. Variable definitions are the same as in table 2.***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE A3
Sample Comparisons

Panel A: 2010–2017

	LinkedIn		I/B/E/S	Diff.	
	(1)	(2)	(3)	(1) − (2)	(1) − (3)
Variables	Photo	No Photo			
ACCURACY	0.023	0.021	0.014	0.001	0.008***
I_{STAR}	0.029	0.029	0.008	−0.001	0.021***
GEXP	8.018	8.357	7.298	−0.399	0.720**
FEXP	2.992	3.102	2.769	−0.110	0.223
SIC2	3.022	2.918	2.959	0.104	0.063
PROTFOLIO_SIZE	15.046	15.129	14.875	−0.083	0.171
BROKER_SIZE	69.331	68.971	69.168	0.360	0.163
SIZE	15.028	15.122	14.766	−0.094*	0.262***
BM	0.523	0.564	0.669	−0.041	−0.146***
No. analyst	582	557	4,343		

Panel B: 1990–2017

	LinkedIn		I/B/E/S	Diff.	
	(1)	(2)	(3)	(1) − (2)	(1) − (3)
Variables	Photo	No Photo			
ACCURACY	0.024	0.022	0.012	0.002	0.012***
I_{STAR}	0.045	0.043	0.009	0.002	0.036***
GEXP	5.924	6.072	5.259	−0.148	0.665***
FEXP	2.252	2.296	2.036	−0.044	0.216***
SIC2	2.826	2.730	2.733	0.096	0.093
PROTFOLIO_SIZE	14.823	14.494	14.298	0.329	0.525**
BROKER_SIZE	69.316	69.574	69.590	−0.258	−0.274
SIZE	14.813	14.871	14.480	−0.058*	0.333***
BM	0.566	0.556	0.639	0.010	−0.073
No. analyst	795	760	7,872		

This table provides the grouped *t*-test result for analyst-level characteristics between the samples of LinkedIn analysts with and without profile photos, and between the samples of LinkedIn and I/B/E/S analysts. Panels A and B correspond to the sample periods of 2010–2017 and 1990–2017, respectively. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE A4

Robustness Checks: Alternative Measures of Face Factors, Fixed Effects, and Error Clustering

Panel A: Face factors and forecast accuracy

	No Orthogonalization (1)	Alternative Ordering of Orthogonalization: *ATT-TRUST-DOM* (2)	Alternative Ordering of Orthogonalization: *DOM-TRUST-ATT* (3)	Analyst Age Fixed Effects (4)	Standard Errors Clustered by Analyst (5)	Two-Way Clustered Standard Errors by Firm and Year (6)	Alternative Accuracy Measure: AFE (7)
TRUST	3.529***	3.048**	3.333**	3.567***	3.151*	3.151*	0.331*
	(2.58)	(2.18)	(2.37)	(2.55)	(1.84)	(1.81)	(1.95)
ATTRACT	2.698	−2.142	2.524	−1.801	−2.004	−2.004	−0.353
	(1.06)	(−0.93)	(1.06)	(−0.78)	(−0.43)	(−0.81)	(−1.46)
DOM	9.855***	8.524***	8.109***	7.445***	6.647**	6.647**	0.521**
	(3.92)	(3.92)	(3.61)	(3.46)	(1.98)	(2.44)	(2.17)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.064	0.064	0.064	0.064	0.064	0.064	0.484
N	248,523	248,523	248,523	248,523	248,523	248,523	241,283

Panel B: Face factors and market reactions to analyst forecast revisions

	No Orthogonalization (1)	Alternative Ordering of Orthogonalization: *ATT-TRUST-DOM* (2)	Alternative Ordering of Orthogonalization: *DOM-TRUST-ATT* (3)	Analyst Age Fixed Effects (4)
REVISION × *TRUST*	0.370**	0.382**	0.366**	0.367**
	(2.00)	(2.00)	(1.98)	(1.98)
REVISION × *ATTRACT*	0.033	0.010	0.031	0.039
	(0.12)	(0.04)	(0.12)	(0.15)
REVISION × *DOM*	−0.015	−0.013	−0.060	−0.012
	(−0.05)	(−0.05)	(−0.23)	(−0.05)
Controls and revision × Controls	Yes	Yes	Yes	Yes

(*Continued*)

TABLE A4—*(Continued)*

Panel B: Face factors and market reactions to analyst forecast revisions

	No Orthogonalization (1)	Alternative Ordering of Orthogonalization: *ATT-TRUST-DOM* (2)	Alternative Ordering of Orthogonalization: *DOM-TRUST-ATT* (3)	Analyst Age Fixed Effects (4)
FE and revision × FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.018	0.018	0.018	0.018
N	85,643	85,643	85,643	85,643

Panel C: Face factors and All-Star Analyst selection outcomes

	No Orthogonalization (1)		Alternative Ordering of Orthogonalization: *ATT-TRUST-DOM* (2)		Alternative Ordering of Orthogonalization: *DOM-TRUST-ATT* (3)		Analyst Age Fixed Effects (4)	
	Male	Female	Male	Female	Male	Female	Male	Female
TRUST	0.415	−0.567	−0.792	1.858	0.405	−0.525	0.267	−1.195
	(0.86)	(−0.73)	(−1.45)	(1.41)	(0.85)	(−0.68)	(0.54)	(−1.31)
ATTRACT	0.120	−0.581	0.314	−0.273	0.112	−0.544	−0.782	0.932
	(0.19)	(−0.35)	(0.63)	(−0.36)	(0.19)	(−0.35)	(−1.40)	(0.78)
DOM	1.899**	−5.179***	1.643**	−4.479***	1.803**	−4.816***	1.689**	−6.812***
	(2.20)	(−3.35)	(2.20)	(−3.35)	(2.39)	(−4.35)	(2.25)	(−4.15)
Test of coef. equality(DOM)	$\chi^2 = 16.03 (p = 0.000)$		$\chi^2 = 16.03 (p = 0.000)$		$\chi^2 = 24.43 (p = 0.000)$		$\chi^2 = 22.22 (p = 0.000)$	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.501	0.470	0.501	0.470	0.501	0.470	0.511	0.0510
N	5,030	687	5,030	687	5,030	687	5,030	687

This table presents results of robustness checks, with panels A, B, and C corresponding to tables 2, 7, and 9, with the same dependent and independent variables, fixed effects, and clustering of standard errors, respectively, unless otherwise mentioned. In column 1, we replace the face factors with the nonorthogonalized factors. In columns 2 and 3, we use face factors obtained with alternative orthogonalization orders: *ATT-TRUST-DOM* and *DOM-TRUST-ATT*, respectively. Column 4 includes age fixed effects, column 5 presents the *t*-statistics computed with standard errors clustered by analyst, and column 6 uses two-way clustered standard errors by firm and by year. Column 7 uses an alternative analyst forecast accuracy measure, *ACCURACY-AFE*). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE A5

Robustness Checks: Measurement Errors by Photo Editing and Stale Photos

Panel A: Face factors and forecast accuracy

	(1) Excluding Edited Photos	(2) Recent Period 2007–2017
	ACCURACY	*ACCURACY*
TRUST	2.738**	4.975**
	(1.96)	(2.44)
ATTRACT	−1.594	−1.276
	(−0.65)	(−0.41)
DOM	6.682***	9.152***
	(3.33)	(3.40)
Controls	Yes	Yes
Adjusted R^2	0.064	0.051
N	245,544	140,964

Panel B: Face factors and market reactions to analyst forecast revisions

	(1) Excluding Edited Photos	(2) Recent Period 2007–2017
REVISION × *TRUST*	0.349*	0.356*
	(1.89)	(1.65)
REVISION × *ATTRACT*	0.087	0.106
	(0.35)	(0.36)
REVISION × *DOM*	−0.028	−0.271
	(−0.12)	(−0.96)
Controls and revision × Controls	Yes	Yes
FE and revision × FE	Yes	Yes
Adjusted R^2	0.018	0.019
N	84,613	60,472

Panel C: Face factors and All-Star Analyst selection outcomes (excluding edited photos)

	I_{STAR} *(Male)*		I_{STAR} (Female)
TRUST	0.363		−0.353
	(0.75)		(−0.47)
ATTRACT	−0.790		1.851
	(−1.43)		(1.41)
DOM	1.640**		−4.363***
	(2.20)		(−3.35)
Test of coef. equality (DOM)		$\chi^2 = 16.06$ ($p = 0.0001$)	
Controls	Yes		Yes
Adjusted R^2	0.503		0.470
N	4,953		687

This table presents the results of robustness checks that exclude edited profile pictures or stale observations. Panels A, B, and C correspond to tables 2, 7, and 9, with the same dependent and independent variables, fixed effects, and clustering of standard errors, respectively, unless otherwise mentioned. In column 1, we exclude analyst observations with an editing probability of 10% or higher. In column 2, we focus on the more recent sample period of 2007–2017.***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE A6

Face Factors and Market Reactions to Analyst Forecasts: Alternative CAR Windows

	CAR[−1, +1]		*CAR*[−1, 0]		*CAR*[0, 0]	
REVISION	–	–	–	–	–	–
REVISION × *TRUST*	0.179	(0.78)	0.033	(0.18)	0.022	(0.15)
REVISION × *ATTRACT*	0.072	(0.25)	0.008	(0.04)	0.048	(0.26)
REVISION × *DOM*	−0.001	(−0.04)	0.017	(0.07)	0.063	(0.33)
REVISION × *TRUST* × I_{HIGH_INST}	0.594*	(1.69)	0.688**	(2.26)	0.492**	(2.19)
REVISION × *ATTRACT* × I_{HIGH_INST}	−0.048	(−0.10)	−0.064	(−0.16)	0.101	(0.33)
REVISION × *DOM* × I_{HIGH_INST}	−0.075	(−0.16)	0.066	(0.16)	−0.130	(−0.44)
REVISION × I_{HIGH_INST}	−0.407	(−1.09)	−0.475	(−1.47)	−0.292	(−1.12)
REVISION × *LAG_ACCURACY*	0.511*	(1.74)	0.384*	(1.69)	0.110	(0.68)
REVISION × *fWHR*	0.476*	(1.68)	0.246	(1.61)	0.204*	(1.73)
Other firm/analyst/forecast characteristics controls	Yes		Yes		Yes	
Revision × Controls	Yes		Yes		Yes	
Revision × Fixed effects	Yes		Yes		Yes	
Adjusted R^2	0.018		0.017		0.012	
N	85,643		85,643		85,643	

This table shows panel regression results on the relation between analyst face factors and market reactions to analyst earnings forecast revisions. The dependent variables are cumulative abnormal return of three windows: *CAR*(−1, +1), *CAR*(−1, 0), *and CAR*(0, 0), respectively. The abnormal returns are calculated as the difference between the individual stock return and the CRSP value-weighted index return. *TRUST*, *ATTRACT*, and *DOM* correspond to the analyst's face factors of trustworthiness, attractiveness, and dominance, respectively, orthogonalized and scaled to [0, 1] within gender. *fWHR* is the analyst's facial width-to-height ratio. *LAG_ACCURACY* is the mean relative accuracy of the analyst's forecast over the last eight quarters. *REVISION* is the difference between the analyst's current and preceding earnings forecast for a firm-quarter, scaled by the stock price two trading days prior to the current forecast date. I_{HIGH_INST} is an indicator variable that equals 1 if a firm's institutional ownership is in the top quartile for the prior industry-year. We include the following control variables: forecast horizon (*HORIZON*), a female indicator (I_{FEMALE}), analyst general and firm-specific experience (*GEXP* and *FEXP*), age (*AGE*), number of firms the analyst follows (*PORFOLIO_SIZE*), size of the brokerage house that the analyst is affiliated with (*BROKER_SIZE*), lagged firm characteristics (return on asset ROA, debt-to-equity ratio *LEVERAGE*, logarithm market capitalization *SIZE*, book-to-market ratio *BM*, one-week buy-and-hold abnormal return *BHAR*). All regressions include a constant, industry fixed effects, and quarter fixed effects. The *t*-statistics are computed with standard errors clustered by firm and reported in parentheses.***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

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