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

Peng L, Teoh S H, Wang Y, et al.

Journal of Accounting Research, 2022.

叶鑫　2022/05/18

Background

- Face impressions: Humans form first impressions about other people from their faces spontaneously within milliseconds.

- 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.

- Attractive people win more legal cases (Zebrowitz et al. 1991), earn a beauty premium (Mobius, 2006), and are more successful in online dating (Finkel et al. 2012). Trustworthy-looking people are more likely to win elections (Todorov et al. 2005).

- There are studies of borrower **trustworthiness** on loan terms (Duarte, 2012), CEO **competence** on compensation (Graham, 2017), analyst **beauty** on forecast accuracy (Cao et al. 2020) and auditor **trustworthiness** on auditor tenure and audit fees (Hsieh et al. 2020).

Motivation

- Information possessors (firm insiders, industry experts, analyst peers) and clients (investors, buy-side analysts) form perceptions about analysts via social interactions.

- We apply the ML algorithms to obtain empirical measures for three key face factors(72%).
  - ➢ TRUST: self-fulling prophecy feedback effect
  - ➢ DOM: self-fulling prophecy feedback effect
  - ➢ ATTRACT: wears off in the long run and is attenuated by professionalism in the relationship.

- 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.

Research Content

- We first examine the associations of the face factors with analysts' forecast accuracy.
  - ➢ Analysts have recently attended events hosted by firms.
  - ➢ An important regulatory change to information access
  - ➢ New and seasoned analysts and new and seasoned CEO/CFOs

- We then examine stock return reactions to forecast revisions of different face factors.
  - ➢ Institutional investors are much more likely than retail investors to have face-to-face meetings with analysts.

- Finally, we examine gender differences for the face factor associations with accuracy and All-Star status.
  - ➢ Do not match societal norms of gender stereotypes tend to elicit strong negative reactions from the observers (Oh, Buck, and Todorov, 2019).

Research Conclusion

- 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.

- 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.

- In sum, face impressions from social interactions have important consequences for information acquisition and information dissemination in the capital markets.

Sample selection

- Our raw sample consists of 4511 US sell-side analysts(IBES & Thomson Reuters Corporation) and the firms they cover in the merged CRSP/COMPUSTAT data set from 1990.01 to 2017.12.

- 1566 maintained a LinkedIn profile as of May 2018, and 795 posted a profile picture. Our final merged sample consists of 248,523 quarterly EPS forecasts and 7038 analyst-year observations for 5847 unique firms.

Panel B: 1990–2017

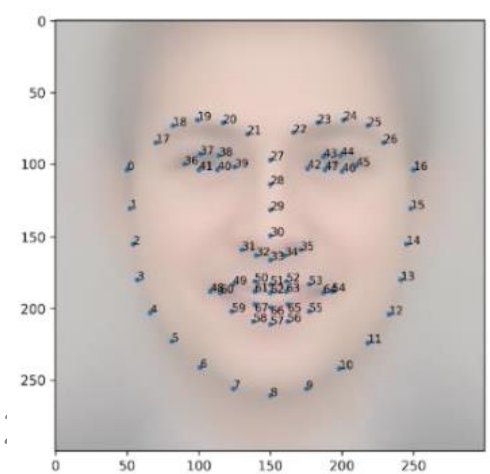
	LinkedIn		I/B/E/S	Diff.	
Variables	(1) Photo	(2) No Photo	(3)	(1)-(2)	(1)-(3)
ACCURACY	0.024	0.022	0.012	0.002	0.012***
I_{STAR}	0.045	0.043	0.009	0.002	0.036***
GEXP	5.924	6.072	5.259	-0.148	0.665***
FEXP	2.252	2.296	2.036	-0.044	0.216***
SIC2	2.826	2.730	2.733	0.096	0.093
PROTFOLIO_SIZE	14.823	14.494	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		

Face Factors Construction

- We first preprocess the analysts' photos to standardize the **size** and **head location** and then apply the facial recognition software, **IBUG**, to each photo to delineate the **68** fiducial landmark points.

- Then, we calculate 3 raw factor scores from **65** attributes extracted from 68 points using Vernon et al. (2014) **ML** model. Last, we **validate** these scores with MTurk human raters.

- To facilitate comparison across the face factors and allow for differences in impressions by the gender of the observed, we **scale** the raw scores to between zero and one by **gender** group.



65 Physical Features (e.g.)

Eyebrow area	Area enclosed by points 17:21, 22:26
Head width	Horizontal distance between centroid of 15:16 and centroid of 0:1
……	……

Variables

- $PMAFE_{i,j}^{q} = \left(AFE_{i,j}^{q} - MAFE_{IBES,j}^{q}\right) /\ MAFE_{IBES,j}^{q}$
- - $PMAFE$: Analyst Forecast Accuracy
- $fWHR$: An analyst's facial width-to-height ratio

- 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 zero and one.

- 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.

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

orthogonalized

Control Variables

- We include a large set of additional controls for analyst, firm, and brokerage house characteristics following past studies on analyst forecast accuracy.
- And We winsorize all continuous variables at the 1% and 99% level.

Variables	**N**	**Mean**	**SD**	**P10**	**P25**	**Median**	**P75**	**P90**
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
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						

1. Face Factors and Analyst Forecast Accuracy

$$\text{ACCURACY}_{i,j,t} = \beta_0 + \beta_1 \text{ Face Factors }_i + \gamma X + \varepsilon_{i,j,t}$$

	(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)
Adj. R^2	0.064	0.064	0.064	0.064
N	248,523	248,523	248,523	248,523

1.1 Information Access Channel — 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.

- $\text{ACCURACY}_{i,j,t} = \beta_0 + \beta_1 \text{ Face Factors }_i + \beta_2 \text{ Face Factors }_i \times I_{MEET} + \gamma X + \varepsilon_{i,j,t}$

	I_{MEET} = *Forecasts Issued After Meetings*	
	(1) *[0, 180]*	(2) *[181, 360]*
TRUST × I_{MEET}	15.220**	8.610
	(2.41)	(1.38)
ATTRACT × I_{MEET}	-5.123	-12.490
	(-0.60)	(-1.61)
DOM × 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
Adj. R^2	0.054	0.054
N	197,051	197,051

5.10%
Green, 2014

1.2 Information Access Channel — Shock from Reg FD

- On October 23, 2000, the SEC implemented Reg FD to prevent selective disclosure of private information by public companies.

- 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.

	(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 × $I_{Pre\text{-}FD}$			6.050*
			(1.67)
ATTRACT × $I_{Pre\text{-}FD}$			-1.970
			(-0.38)
DOM × $I_{Pre\text{-}FD}$			0.610
			(0.10)
$I_{Pre\text{-}FD}$			-1.680
			(-0.34)
Controls	YES	YES	YES
Adj. R^2	0.102	0.060	0.063
N	29,163	219,266	248,523

1.3 New Relationships and Persistence of Face Factor Effects

- We hypothesize that an attractive new face has a strong positive effect on information access, but the effect disappears with time.

- Specifically, we define $I_{INEW\_ANALYST}$ as one if an analyst's industry experience is two years or less, and $I_{INEW_{CEO}/CFO}$ as one if the forecast was made within two years of a new CEO or CFO hire.

	(1) $I = I_{NEW\ ANALYST}$	(2) $I = I_{NEW\ CEO/CFO}$
TRUST × *I*	-3.770	-0.626
	(-1.52)	(-0.26)
ATTRACT × *I*	8.204**	6.146**
	(2.38)	(2.00)
DOM × *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
Adj. R^2	0.064	0.064
N	248,523	248,523

2. Capital Market Outcomes

- We examine whether face factors modulate investors' sensitivity to analyst forecast revisions.
- $$\text{CAR}_{i,j,t} = \beta_0 + \beta_1 \text{ REVISION}_{i,j,t} + \beta_2 \text{ FaceFactors}_i \times \text{REVISION}_{i,j,t} + \delta X + \gamma X \times \text{ REVISION}_{i,j,t} + \varepsilon_{i,j,t}$$
- REVISION: The change in an analyst's forecast from the analyst's prior forecast, scaled by the stock price two trading days prior

	(1)		(2)	
REVISION	0.932**	(1.96)	--	--
REVISION × *TRUST*	0.334*	(1.84)	0.369**	(1.99)
REVISION × *ATTRACT*	-0.037	(-0.15)	0.039	(0.16)
REVISION × *DOM*	0.071	(0.28)	-0.013	(-0.05)
REVISION × *LAG_ACCURACY*	0.534*	(1.81)	0.489*	(1.71)
REVISION × *fWHR*	0.322*	(1.81)	0.332*	(1.89)
Other Firm/Analyst/Forecast Characteristics Controls	YES		YES	
REVISION ×*Controls*	YES		YES	
REVISION × *Fixed Effects*	NO		YES	
Adj. R^2	0.013		0.018	
N	85,643		85,643	

2.1 Price Reactions to Revision: Institutional Ownership

- We expect that the relations between face factors and market reactions to forecast revisions are more pronounced in firms with high institutional ownership which are more likely to have had face-to-face interactions with analysts.
- I_{HIGH_INST} : Equal to one for firms in the top institutional ownership quartile of the Fama-French 17 industry classification for that year

	(3)	
REVISION	--	--
REVISION × *TRUST*	0.179	(0.78)
REVISION × *ATTRACT*	0.072	(0.25)
REVISION × *DOM*	-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*	0.511*	(1.74)
REVISION × *fWHR*	0.476*	(1.68)
Other Firm/Analyst/Forecast Characteristics Controls	YES	
REVISION ×*Controls*	YES	
REVISION × *Fixed Effects*	YES	
Adj. R^2	0.018	
N	85,643	

3. Gender Effects and Labor Market Outcomes

- 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).
- Female analysts who are perceived to be dominant tend to be judged negatively, so the information possessors may be less willing to share 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.

TRUST	3.151**	2.741
	(2.26)	(1.16)
ATTRACT	-2.004	-9.198***
	(-0.88)	(-3.03)
DOM	6.647***	-8.550**
	(3.09)	(-2.17)
fWHR	3.587**	-3.653
	(2.09)	(-1.12)
Controls		YES
Adj. R^2	0.064	0.068
N	248,523	29,333

3.1 Face Factors and All-Star Selection Outcomes

- 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, 2011).

- logit regression: $I_{STAR,i,t} = \beta_0 + \beta_1 \text{ Face Factors } s_i + \beta_2 X + \varepsilon_{i,t}$

	(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)	
Pseudo R^2	0.470	0.501	
N	687	5,030	

Research Conclusion

- 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.

- 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.

- In sum, face impressions from social interactions have important consequences for information acquisition and information dissemination in the capital markets.