Analyst Characteristics, Textual Information and Prediction Accuracy: Evidence from China Financial Market

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Backgrounds

- **Sell-side analyst:**
  - A sell-side analyst works for a brokerage firm and evaluates companies for future earnings growth and other investment criteria;
  - Analyst conduct researches and site-visitations to gather information;
  - **Analyst reports** (*final product*) fulfill analyst's information discovery role and re-interpretation role;
  - They offer/sell their recommendations (Sell, Hold, Buy) in reports to clients (typically, fund managers);

Backgrounds (cont.)

- **Q: What makes an analyst a *good* analyst?**
- **Major Literatures focus on analyst extrinsic traits:**
  - Education, age, experience, affiliated trading house size etc.
  - Industry experience (Bradley et al. 2017)
  - Social connection with top executives (Fang and Huang, 2017)
- **Personality traits have wild applications in fields other than finance:**
  - Politics: predicting election outcomes by judging candidates' facial traits (Joo et al., 2017)
  - Psychology: analyzing memorability by modelling facial traits (Bainbridge, Isola and Oliva, 2013)
- **Attempt measurement: *fWHR*** (Jia et al., 2014; He et al., 2016)

fWHR - facial Width-to-Height Ratio

Jia et al., 2014

Research Questions 1

- **Analyst personality traits and textual reports**
  - Linguistic Evidence: language and personality are interconnected, and personality traits affect various of linguistic productions (Mairesse et al., 2007)
  - What's included in analyst report?
    - Soft information (Qualitative)
      - Textual content could be understood by measuring general **tone** by Naïve Bayes algorithm and(or) specific textual characteristics (Huang, Zang and Zeng, 2014)
    - Hard information (Quantitative)
      - Over-optimism in analyst universe in China (93% buy; 92% reiterate, source: CSMAR)
  - **H1**: Analyst characteristics, both extrinsic and intrinsic, can influence qualitative textual measures, but not quantitative measures.

Research Questions 2

- **How will analyst traits impact their performance on financial market?**
  - Prediction accuracy: absolute forecast error (*AFE*)
  - Certain analyst traits could provides them with benefits both directly and indirectly
    - Hard traits – directly: skills, exps etc. lead to better interpretation role and more accurate predictions
    - Soft traits – indirectly from text: site-visit, social network lead to better discovery role, and more accurate textual reports and then more predictions;

  - **H2:** analyst hard traits and textual content have impacts on their prediction accuracy

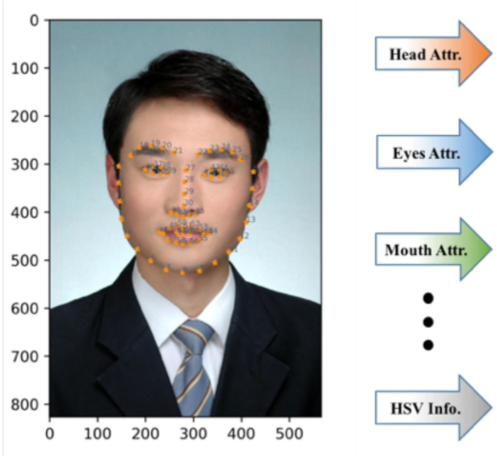
Research Questions 3

- **Long-term effect of traits on analyst career path**
  - Star analyst is still a valid indicator for analyst career path (Bradley et al., 2017; Groysberg, Healy, and Maber, 2011).
  - Being selected as Star Analysts is a ***must*** in major trading houses
  - Channels
    - Greater social network centrality;
    - More information sources
    - Better fulfilling analyst information *discovery* and *re-interpretation* role in financial market

  - **H3:** Analysts with certain personality traits have higher probability to have a favorable career outcome.

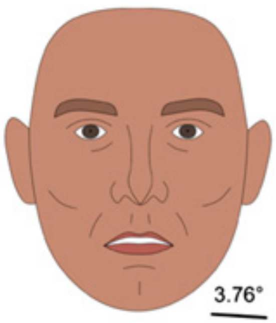
Samples and Variables

- **Analyst Report:**
  - *Tencent* Finance: 309,065 firm-level analyst reports from Jan. 2006 to Aug. 2016 (matching name and brokerages)
- **Analyst Profile Information:**
  - Source:
    - o SAC (Security Association of China)
    - o Over 117,000 analyst profiles from 129 brokerages
  - **Identifying personality traits:**
    - o Locating 68 key facial landmarks
    - o Computing 62 facial attributes
    - o Deriving 3 facial traits (Vernon et. al,. 2014)
      - ✓ Approachability Score
      - ✓ Dominance Score
      - ✓ Youthfulness and Attractiveness Score

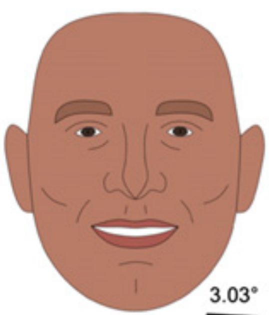


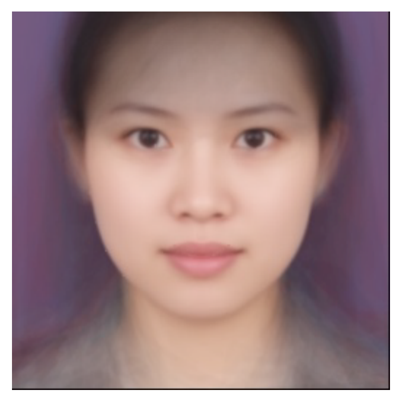
Average Faces (selected)

(low) Approachability (high)



(low) Youthfulness and Attractiveness (high)





Synthesized face-like Images (Vernon et, al., 2014)

Results

H1:

$$OPN = \alpha_0 + \alpha_1 SITE + \beta_1 APPRO + \beta_2 YOAT + \beta_3 DOM + \gamma_1 FEMALE + \gamma_2 EDU + \gamma_3 STAR + \gamma_4 TRSIZE + \sum_j \delta_j Controls_j + \varepsilon$$

	OPN (t-stats)	**REC_CNG (t-stats)**	**FEPS_CNG (t-stats)**
SITE	0.0788*** (9.49)	0.0045 (0.48)	0.0108 (1.24)
APPRO	-0.0009*** (-3.84)	0.0002 (1.10)	-0.0002 (-0.94)
YO_AT	0.0136*** (2.65)	0.0017 (0.36)	0.0080 (1.35)
DOM	0.0222*** (2.64)	0.0048 (0.59)	0.0079 (1.00)
Adj. R^2	12.72%	1.30%	1.58%
Obs.	12,203	10.545	12,203

$$Textual\ Characteristics = \alpha_0 + \alpha_1 SITE + \beta_1 APPRO + \beta_2 YOAT + \beta_3 DOM + \gamma_1 FEMALE + \gamma_2 EDU + \gamma_3 STAR + \gamma_4 TRSIZE + \sum_j \delta_j Controls_j + \varepsilon$$

	TITLE (t-stats)	LENGTH (t-stats)	CONCISE (t-stats)	FIN (t-stats)	COMPLEX (t-stats)	CONFI (t-stats)
SITE	0.1318*** (4.63)	1.0541** (2.17)	-0.1830 (-0.53)	-0.5869*** (-6.63)	-0.2214 (-0.14)	0.1000 (1.06)
APPRO	-0.0002 (-0.25)	0.0356*** (2.88)	-0.0206** (-2.33)	0.0040* (1.71)	0.0085 (0.38)	0.0003 (0.15)
YO_AT	0.0069 (0.34)	-0.0162 (-0.06)	-0.3110* (-1.68)	-0.2618*** (-4.86)	-0.8583 (-1.59)	0.0471 (1.10)
DOM	0.0918*** (2.87)	-0.6296 (-1.46)	0.7273** (2.52)	-0.1348 (-1.22)	-0.2355 (-0.21)	0.1600** (2.35)
STAR	0.0251 (1.20)	-0.9571*** (-3.18)	-0.0274 (-0.14)	0.0368 (0.58)	5.2141*** (5.78)	0.1250** (2.31)
FEMALE	0.0427* (1.68)	0.5318 (1.52)	0.2328 (0.92)	0.3615*** (4.70)	-3.8749*** (-3.87)	-0.1402** (-2.57)
EDU	0.0255 (1.39)	1.2470*** (4.36)	-0.4878** (-2.48)	0.2612*** (4.00)	-1.0548 (-1.40)	-0.0226 (-0.51)
Adj. R^2	3.45%	15.18%	9.15%	14.58%	10.32%	19.03%
Obs.	12,203	12,203	12,203	12,203	12,203	12,203

Results (cont.)

H2:

$$(Absolute)\ Forecast\ Error = \alpha_0 + \alpha_1 OPN + \alpha_1 SITE + \alpha_1 OPN \times SITE + \gamma_1 FEMALE + \gamma_2 EDU + \gamma_3 STAR + \gamma_4 TRSIZE + \sum_j \delta_j Controls_j + \varepsilon$$

	FE (t-stats)	**AFE (t-stats)**
OPN	-0.0010* (-1.89)	-0.0013*** (-3.12)
SITE	0.0006 (0.60)	0.0002 (0.33)
*OPN * SITE*	0.0021* (1.69)	0.0025*** (2.78)
FEMALE	-0.0009*** (-3.57)	-0.0009*** (-4.06)
EDU	-0.0006** (-2.36)	-0.0006*** (-2.64)
Adj. R^2	17.87%	30.74%
Obs.	51,804	51,804

Results (cont.)

H3:

$$P(Star = 1) = \alpha_0 + \beta_1 APPRO + \beta_2 YOAT + \beta_3 DOM + \gamma_1 AFE + \gamma_2 CAR0\_1 + \gamma_3 SITE + \gamma_4 EXPER + \gamma_5 FEMALE + \gamma_6 MIX + \gamma_7 TRSIZE + \sum_j \delta_j Controls_j + \varepsilon$$

	1.Coefficients (z-stats)	**2.Coefficients (z-stats)**	**1.dy/dx (z-stats)**	**2.dy/dx (z-stats)**
APPRO	-0.0054*** (-3.59)	-0.0059*** (-3.91)	-0.0013*** (-3.59)	-0.0014*** (-3.92)
YO_AT	0.5396*** (15.78)	0.5436*** (15.69)	0.1275*** (15.86)	0.1271*** (15.77)
DOM	0.4666*** (8.42)	0.4554*** (8.14)	0.1103*** (8.43)	0.1065*** (8.15)
AFE	-1.6281** (-2.17)	-1.6383** (-2.17)	-0.3848** (-2.17)	-0.3830** (-2.18)
CAR0_1	-0.2069 (-0.71)	-0.2733 (-0.93)	-0.0489 (-0.71)	-0.0639 (-0.93)
Text Chars.	N	Controlled	N	Controlled
Obs.	11,093	11,093	11,093	11,093

- **Robustness check**: year-average level

$$P(Star = 1) = \alpha_0 + \beta_1 APPRO + \beta_2 YOAT + \beta_3 DOM + \gamma_1 EXPER + \gamma_2 FEMALE + \gamma_3 MIX + \gamma_4 TRSIZE + \gamma_5 NUMFIRMS + \theta_1 SIZE\_y + \theta_2 AFE\_y + \theta_3 CAR\_y + \sum_j \delta_j Controls_j + \varepsilon \qquad (6)$$

	Coefficients (z-stats)	**dy/dx (z-stats)**
APPRO	-0.0052 (-1.04)	-0.0011 (-1.04)
YOAT	0.3796*** (3.98)	0.0836*** (3.98)
DOM	0.4191** (2.32)	0.0923** (2.31)
EXPER	0.1324*** (2.85)	0.0292*** (2.85)
FEMALE	-0.5552*** (-3.59)	-0.1223*** (-3.66)
Adj. R^2	25.12%	
Obs.	803	803

Conclusions

- Analysts personality traits are associated with their general textual reports tone and specific textual characteristics

- Certain characteristics may bring them more private information and subsequently lower observed prediction errors, but not after site-visit

- Analysts with certain characteristics are more likely to have favorable career outcome

Contributions

- We introduce a novel perspective to understand financial market participants by analyzing their personality traits.

- We also document that Naïve Bayes algorithm NLP approach is also effective in Chinese context in China Financial market.