Beauty Premium? Evidence from Institutional Investors' Voting for All-Star Analysts

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ABSTRACT

This study examines whether institutional investors' voting for All-Star financial analysts is affected by analyst beauty. Using a sample of 1,135 U.S. analysts and controlling for analyst performance, we document that beauty, on average, does not affect the outcome of All-Star analyst voting. However, a beauty premium emerges in those sectors where there is high information asymmetry on analyst performance between analysts and fund managers. We further find that good-looking female U.S. analysts are less likely to be voted All-Star analysts. Our evidence implies that the beauty premium can be mitigated by a strong economic force such as low information asymmetry.

JEL Classification: D83, G11, G24, J24, J44, M41

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1. Introduction

Many people believe that a beauty premium is universal and economically significant. A large literature in economics and psychology indeed finds that people are often rewarded for their attractiveness. For example, physically attractive workers earn more than other workers (Hamermesh and Biddle 1994, Mobius and Rosenblat 2006) and good-looking job candidates are more likely to get calls from employers (Ruffle and Shtudiner 2015). However, few studies empirically test whether this beauty premium is due to a rational economic force or a behavioral bias. In this paper, we take advantage of the setting of institutional investors' voting for All-Star analysts to examine whether a beauty premium exists in the financial industry and the underlying mechanism of this beauty premium.[1] All-Star analyst voting, started by *The Institutional Investor* in 1975, has gained a significant reputation among investors over the past four decades. While the voting largely depends on the research quality of sell-side analysts, it could also be affected by other factors such as beauty.[2]

Prior studies offer several potential explanations for the beauty premium. First, the beauty premium may be driven by information asymmetry among employers and/or customers on workers' performance. Previous research finds that beauty is an indirect measure for unobservable skills or ability and physically attractive workers may be more capable and confident (e.g., Eagly et al. 1991, Mobius and Rosenblat 2006, Hamermesh 2011). The premium is high when workers' performance is difficult to observe. Second, the beauty premium may be driven by the tastes of employers and/or customers. Some employers and/or customers prefer good-looking workers even if they have full knowledge of the workers' performance. Third, the beauty premium may be driven by self-selection. Good-looking workers are more likely to self-select into highly rewarding professions.

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[1] We define beauty premium in a broad sense in this study, i.e., physically attractive analysts are more likely to be voted as All-Stars.

[2] For example, analysts are known to lobby fund managers heavily before the voting (Hong and Kubik 2003).

If the beauty premium is driven by information asymmetry, it can be reduced or eliminated in a highly competitive market where performance is more transparent for employers and customers. However, if the beauty premium is due to a behavioral bias and proxies for some unobservable characteristics, we should find a beauty premium even in a highly competitive environment where information asymmetry is low.

The financial analyst profession is very competitive, with a high turnover rate. Anecdotal evidence suggests that nearly half of all analysts leave their jobs within three years. All-Star analyst voting is also competitive, as only several top analysts in each industry sector are recognized as All-Stars each year. Regular earnings forecasts and stock recommendations reduce the information asymmetry related to analyst performance between analysts and investors. As such, this is the ideal setting to test the underlying mechanism of the beauty premium.

Our sample consists of 1,135 U.S. analysts participating in an All-Star analyst voting process during the years 2013 to 2015. We manually collect the photos of the analysts from their LinkedIn pages. To analyze these photos, we employ Amazon Mechanical Turk (MTurk) service, an online service through which individual workers can perform standardized tasks with compensation (Duarte et al. 2012). Each analyst photo is rated, on average, by 10 MTurk workers. In robustness analysis, we use 610 undergraduate and MBA business students from a major research university in North America as photo raters. Each photo is rated by 20 students on average.

Our results show that beauty, on average, does not affect the likelihood of being voted as an All-Star analyst. We find consistent results when analyst beauty is measured based on raw quantitative scores (scale from 1 to 100), quantitative scores mean-adjusted at the rater level, and raw qualitative scores (below average, average, attractive, very attractive). Our results are robust across both MTurk and student raters.

Motivated by Andreoni and Petrie's (2008) experimental finding that beauty has different effects on male and female subjects, we find that while female analysts are more likely to be voted as All-Star analysts (Kumar 2010), attractive female analysts are discounted in the All-Star voting process.

We further examine whether information asymmetry about analyst performance affects the beauty premium. We construct a composite index of industry-level information asymmetry based on a principal component analysis of the total number of analyst forecasts, the dispersion of analyst forecasts, and the average experience of analysts in an industry sector and year. Based on the median of this composite index, an industry is classified as either high or low information asymmetry. Our results suggest that while good-looking male analysts receive no beauty premium in sectors with low information asymmetry, they are more likely to be voted as star analysts in sectors with high information asymmetry.[3] Overall, our findings suggest that the beauty premium is muted when fund managers have better information about analyst performance.

Our results persist after controlling for a host of widely documented analyst, brokerage, and firm characteristics, including forecast error, forecast frequency, forecast horizon, experience, portfolio complexity, broker size, firm size, market-to-book ratio, and return on assets. Taken together, our results suggest that the beauty premium, on average, does not exist in the highly competitive market of All-Star analysts. Our additional tests provide evidence consistent with the notion that the beauty premium is driven by information asymmetry as to analysts' performance among analysts and investors.

Our study contributes to several streams of literature. First, it expands our knowledge about the beauty premium. Most economics and psychology studies on beauty employ experimental settings that may not be generalizable to a highly competitive profession. Our study is the first large-sample empirical study documenting that the beauty premium is not universal. Our findings support the assertion that the beauty premium is mainly driven by information asymmetry on performance, and that industry competition helps to reduce the beauty premium by lowering information asymmetry among different parties.

[3] In untabulated tests, we use (1) the number of analysts, (2) the number of analyst earnings forecasts, (3) the number of analyst recommendations, and (4) both the number of analyst earnings forecasts and the number of analyst recommendations in an industry-year to proxy for information asymmetry. We continue to find a significant beauty premium for male analysts in the high information asymmetry industry sectors.

Second, our study contributes to the financial economics literature. Our study is the first to examine the role of beauty in a financial analyst's career advancement. Our results show that financial analysts with better looks do not enjoy a beauty premium in All-Star analyst voting. In contrast, we document the known "dumb blonde" stereotype in the U.S. financial industry, i.e., that attractive female analysts receive a "beauty penalty."

Section 2 discusses the related literature and develops the hypotheses. Section 3 describes the sample and the methodology. Section 4 presents the empirical results. Section 5 discusses the additional tests. Section 6 concludes.

2. Related Literature and Hypotheses

2.1 Beauty Perception

Beauty perception has attracted attention from researchers for the past four decades. These studies typically link beauty to social or intellectual competence. Prior studies suggest that good-looking people are believed to have a variety of positive personal traits, such as health, concern for others, loyalty, ambition, and integrity. Goldman and Lewis (1977) conduct an experiment involving a decision-making scenario, in which college students were asked to rate their telephone partners for social skills and desirability for future contact after three telephone conversations. These college students were also asked to rate themselves on a 10-point physical attractiveness scale. They find that the more physically attractive students received higher ratings from their telephone partners. Eagly et al. (1991) conduct a meta-analysis of the literature and suggest that physical attractiveness is associated with being ambitious, hard-working, generous, honest, trustworthy, confident, and happy. Feingold (1992) summarizes the experimental research on physical attractiveness and concludes that physical attractiveness has a robust correlation with social skills, popularity, intelligence, and mental health. Eagly et al. (1991) also point out that culture helps link physical attractiveness to these positive qualities. For example, in the U.S., the media associate beauty with good things (e.g., a beautiful princess) and ugliness with bad things (e.g., an ugly witch).

2.2 Beauty Premium in the Labor Market

The study by Hamermesh and Biddle (1994) is a seminal work examining the effect of beauty on the labor market. They obtain the appearance rating and salary information of survey participants from the 1977 Quality of Employment Survey (QES), the 1971 Quality of American Life survey (QAL), and the 1981 Canadian Quality of Life study (QOL). They find a beauty premium for both the U.S. and Canadian samples. Their results show that good-looking workers earn 10-15% more than plain-looking workers. Biddle and Hamermesh (1998) further focus on law school graduates as a specific profession and find that good-looking attorneys earn more than their less attractive peers. Deryugina and Shurchkov (2015) find that the beauty premium is more pronounced in bargaining tasks.

A growing literature is investigating the role of beauty in the hiring process. Boo et al. (2013) submit fictitious CVs with fictitious faces to real job openings, manipulating the level of attractiveness of each photo by computer. They find that physically attractive people receive 36% more callbacks than less attractive people. Ruffle and Shtudiner (2015) further investigate whether beauty has the same effect for female and male candidates in the hiring process. They find that employers are more likely to call back good-looking male candidates, and that good-looking female candidates do not enjoy the same beauty premium due to discrimination from female staff at the employer companies.

Prior research has also shown that beauty can predict election results. Todorov et al. (2005) show that politician appearance predicts the winner in 71.6% of U.S. Senate elections. Berggren et al. (2010) asked 10,011 survey respondents to rate the physical attractiveness of 1,929 Finnish political candidates. Their findings suggest that a one-standard-deviation increase in physical attractiveness is associated with a 20% increase in the number of votes for non-incumbent candidates.

A few recent studies have also documented a beauty premium in corporate settings. For example, Halford and Hsu (2014) find that physically attractive CEOs are correlated with higher returns upon their job announcements, and better acquirer returns on acquisition announcements. Graham et al. (2016) show that CEOs with a “look of competence” enjoy higher compensation. Cao et al. (2016) find that physically attractive Chinese financial analysts make more accurate earnings forecasts and more informative stock recommendations.

2.3 All-Star Analyst Voting

Each year in the U.S., *Institutional Investor* magazine surveys a large number of buy-side fund managers and asks them to vote for the All-Star sell-side analysts. The vote is only open to a proprietary database, consisting of the global top fund managers for pension and hedge funds.[4] *Institutional Investor* does not accept nominations for All-Star analysts; rather, it allows the fund managers to vote for any sell-side participants who publish investment research and distribute it to clients during the period covered by the poll. The voting results are solely determined by numerical score. As per *Institutional Investor*, the final score for each financial analyst is constructed by weighting each vote based on the voter's equity and/or fixed-income assets.[5] The survey asks buy-side fund managers to evaluate the quality of sell-side analysts based on eight to twelve attributes, such as industry knowledge, earnings forecasts, stock picks, accessibility, and responsiveness. The voting results from the surveys are powerful determinants of sell-side analyst payment and career advancement opportunities. Groysberg et al. (2011) find that All-Star analysts earn 61% higher compensation than other analysts. Brown et al. (2015) suggest that All-Star analysts gain more access to management and enjoy stronger bargaining power when they obtain promotions or switch jobs.[6] Analysts are known to lobby fund managers heavily before the voting (Hong and Kubik 2003, Dorfman 1988, Ip 1998, and Kessler 2001).[7]

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[4] Details on the list of fund managers can be found at: http://www.institutionalinvestor.com/ResearchRankLanding.html?typ=c&cat=4#/.V3YR8fl95D8

[5] More details on the voting requirements and process can be found on the website of *Institutional Investor* magazine: http://www.institutionalinvestor.com/

[6] A growing literature examines the effects of social networks on capital markets. For example, Cohen et al. (2010) show that analysts who have alumni-ties with managers are more likely to be voted as All-Star. Fang and Huang (2017) suggest that alumni ties between managers and analysts benefit male analysts more than female analysts in terms of their performance and career outcomes.

[7] Anecdotal evidence suggests, at least in earlier years, that analysts visit most funds to lobby for voting every year, including small funds that do not get analyst visits often and only receive reports regularly. The *Wall Street Journal* (May 14, 1998, p. C1) reports that "Gregg Tenser, head of Pittsburgh-based mutual-fund manager Federated Investors, says his firm receives a surge in calls from analysts wanting to visit between February and May. 'It's the Institutional Investor tour.'" A research director says that all his analysts are out on the road making annual

The All-Star analyst rankings in the U.S. provide a perfect setting to examine whether a beauty premium exists in the highly competitive financial industry. We can trust the integrity of the ranking process, as its importance is not lost on buy-side analysts: they rely on the performance and skills of sell-side analysts to analyze industries and firms, and their votes make a difference in determining which sell-side analysts get promoted. We can also confidently assert that the sell-side analyst industry is indeed highly competitive: many analysts cover the same industry sectors, and the turnover rate within the industry is extremely high.

To summarize, we generate our first null hypothesis as follows.

H1: Beauty does not affect the likelihood of being voted as an All-Star analyst.

2.4 "Dumb Blonde" Stereotype

Beauty may not always help. One example is the "dumb blonde" stereotype, which is prevalent in U.S. culture. In this stereotype, good-looking females are perceived to rely on their looks rather than on intelligence to advance (Ruffle and Shtudiner 2015). As a result, attractive female workers are perceived to have some negative traits and receive a beauty penalty in the labor market. Prior studies suggest that beautiful females are more likely to be seen as egotistical, snobbish and unsympathetic. Agthe et al. (2010) document that attractive candidates tend to be rated lower than unattractive candidates by same-sex evaluators. Ruffle and Shtudiner (2015) find that physically attractive female job candidates receive a lower rate of callbacks than other female candidates. However, in the highly competitive financial industry, it is an empirical question whether this type of discrimination against beautiful women still exists. In the analyst literature, Kumar (2010) documents that female analysts have better-than-average skills when they enter the profession and perform significantly better than their male counterparts.

To summarize, we generate our second null hypothesis as follows.

H2: There is no differential impact of gender on the relationship between beauty and the likelihood of being voted an All-Star analyst.

pilgrimages to see clients and implicitly lobbying for Institutional Investor votes (The *Wall Street Journal* October 29, 1991, p. C1).

2.5 Source of Beauty Premium

Economic and psychology studies provide several potential explanations for the beauty premium. The beauty premium may be driven by information asymmetry among employers or customers on workers' performance. They believe that physically attractive workers have superior skills, which can strengthen their performance. For example, employers, customers, or other related parties believe that good-looking workers are more capable. Reingen and Kernan (1993) find that discrimination by customers can increase the sales of attractive sellers. Likewise, Hamermesh and Biddle (1998) find that judges or juries may decide cases more frequently in favor of attractive attorneys. The belief that physically attractive workers have superior skills makes the premium for beauty high when performance is difficult to measure or observe. The research on beauty perception also suggests that beauty is used as an indirect measure of unobservable characteristics. Some employers or customers still prefer good-looking workers even if they have full information about their performance.

In our first hypothesis, we conjecture that there is no beauty premium in All-Star analyst voting due to the competitive nature of the industry. Strong competition leads to low information asymmetry about analysts' performance. All-Star analyst voting is thus a nice setting for identifying the source of the beauty premium because the level of information asymmetry between analysts and fund managers on analyst performance varies across industries. In particular, if an industry has more analyst reports, less dispersed analyst opinions, and more experienced analysts, fund managers should be more able to assess analysts' performance.

If the beauty premium is driven by information asymmetry, we should observe this premium in industries characterized by high information asymmetry, where there are fewer earnings forecasts (i.e., less analyst performance information), more dispersed earnings forecasts (i.e., greater uncertainty of analyst performance information), and fewer experienced analysts (i.e., fewer track records of analyst performance). However, if the beauty premium is due to behavioral bias, we should find a beauty premium even when information asymmetry is low. We exclude the self-selection explanation because we focus only on the analyst profession.

To summarize, we generate our third null hypothesis as follows.

H3: There is no differential impact of information asymmetry on the relationship between beauty and the likelihood of being voted as an All-Star analyst.

3. Sample Selection and Beauty Measure

3.1. Sample Selection

We use a sample of U.S. analysts to test our hypotheses. Table 1 shows the sample selection procedure. We first retrieve their names from the Thompson Reuters Institutional Brokers' Estimate System (I/B/E/S) recommendation file, and then collect their photos from their LinkedIn profiles. The analyst photos in our sample are reasonably standardized, with (1) 94% of the photos featuring head and upper body, (2) 93% of the photos being color photos, and (3) 90% of the analysts wearing a suit/shirt/dress.[8] Among the 4,377 names of sell-side analysts available from I/B/E/S for the years 2014 to 2015, we are able to identify 1,427 analyst LinkedIn profiles with high-quality photos for rating purposes.[9] These 1,427 profiles map to 3,695 analyst-years for the period of 2013 to 2015. Our final sample consists of 2,772 analyst-years, representing 1,135 distinct analysts. This smaller final sample is due to a combination of factors, including: 1) I/B/E/S data restrictions; 2) Compustat data restrictions; and 3) the requirement of at least one All-Star analyst in an industry per year.

3.2. Measuring Beauty

Our measure of analyst beauty is based on the analysts' facial attractiveness as perceived by the raters. Each analyst photo is rated on two complementary dimensions: (1) quantitative: a scale from 1 to 100; and (2) qualitative: below average, average, attractive, and very attractive.

[8] In a robustness check, we repeat our empirical analysis with the analyst photos that meet all three conditions and the inferences remain unchanged.
[9] We extend the analyses on these same analysts to 2013.

3.2.1 Methodology

The ratings of analyst beauty are obtained from Amazon Mechanical Turk (MTurk), a crowdsourcing internet marketplace that enables businesses and individuals to coordinate the use of human intelligence to perform tasks. In this marketplace, workers can browse jobs and complete them for a monetary payment set by the employer. As noted above, each analyst photo is rated on both a quantitative and a qualitative dimension.

Each analyst photo is rated, on average, by 10 MTurk workers. The actual number of ratings per photo varies slightly because a random number generator is used to select photos for each rater. We measure analyst beauty as the average of the independent quantitative scores received for the analyst, after excluding raters of inconsistent rating quality and dropping the highest and lowest rating for each analyst.[10] The use of a composite rating is consistent with prior work, which shows that the estimated coefficients on beauty are smaller when based on the evaluations of a single rater rather than a composite measure. Composite measures are more reliable because they are based on aggregations of correlated responses.

One potential issue with the raw quantitative beauty measure is that each rater may have different benchmarks for beauty, which would add noise to the measure. To address this concern, we use the quantitative scores mean-adjusted at the individual rater level to proxy for analyst beauty. Specifically, we subtract the mean quantitative score given by a rater from each quantitative score received from the same rater; then, we recalculate the average of such mean-adjusted quantitative scores for each analyst.[11] We also complement the mean-adjusted quantitative beauty measure with the alternative beauty measures based on the raw quantitative scores and the raw qualitative scores. The latter alternative measure is

[10] To control the quality of rating results, we only include raters' scores in our final sample if their ratings are of consistent quality. We proxy for consistent quality in two ways: (1) the correlation between quantitative and qualitative ratings for a given rater is at least 0.60; and (2) the standard deviation of quantitative scores for all photographs coded by an individual is at least 6 (quantitative scores range from 0 to 100). While these cutoffs are admittedly somewhat arbitrary, they seem reasonable based on our review of the raw data.

[11] The mean-adjusted quantitative scores remove the potential effects of a rater's demographic characteristics. See next subsection for details.

calculated as the average independent qualitative rating received for each analyst (i.e., we code "below average" as 1, "average" as 2, "attractive" as 3, and "very attractive" as 4). This alternative beauty measure also deals with the concern that raters may give different quantitative scores to analysts. In addition to the MTurk ratings, we obtain students' ratings. The student subjects consist of over 700 undergraduate and MBA business students from a major research university in North America.[12] Each analyst photo is rated by 20 students on average.

3.2.2 Summary Demographics of Raters

The average age of the MTurk raters is 36 and 57% are male. For ethnicity, 64% of the raters are white/Caucasian, 9% are African-American, and 20% are Asian. To examine the effect of these demographic characteristics on the received ratings of analyst beauty, we regress the raw quantitative scores of analyst beauty on raters' age, gender, and ethnicity. The results show that the raters' age is positively associated with the raw quantitative scores of analyst beauty (p-value < 0.1), but their gender and ethnicity have no significant effects. Importantly, when we regress the mean-adjusted quantitative scores of analyst beauty on the raters' age, gender, and ethnicity, none of these demographic characteristics has a significant effect. These results are consistent with previous research that suggests little cross-cultural variation in people's perceptions of which facial characteristics are attractive (e.g., Langlois et al. 2000, Perrett et al. 1994). As such, we believe that the mean-adjusted quantitative beauty measure is sufficiently unbiased. In addition, as raters are highly unlikely to know the identity of the individuals they are rating, we are not concerned that familiarity will bias the results.

3.3 Summary Statistics for Beauty Measures

Panel A of Table 2 reports the summary statistics of the raw quantitative and qualitative beauty measures based on either MTurk or student ratings. Focusing on the raw quantitative measure, we find that both the mean and median of the MTurk ratings are approximately 50. In contrast, we find that

[12] These students were sourced from an introductory managerial accounting course, an advanced financial accounting course, and an accounting theory course. Ethics clearance was obtained from the Research Ethics Board of the university.

students' ratings, on average, are downward-biased, with mean raw scores of approximately 44. We consider the MTurk ratings to be more diversified and representative for our empirical analyses, so we only report results based on MTurk ratings. While students are systemically more conservative than MTurk workers in their ratings, the relative rankings for analysts are remarkably consistent across both MTurk raters and student raters.

Panel B of Table 2 reports the summary statistics of the raw quantitative and qualitative beauty measures by gender and by All-Star analyst award status. When classifying analysts by gender, we find that female analysts, on average, are perceived to be better looking than male analysts. For example, focusing on the raw quantitative beauty measure, the average scores for male and female U.S. analysts are 48.32 and 60.20, respectively, and this difference is statistically significant (p-value < 0.01). Next, when classifying analysts by All-Star analyst award status, we find that there is no significant difference between the raw quantitative beauty measures of star and non-star analysts. The qualitative measure yields similar results. This finding provides univariate evidence consistent with H1.

Panel C of Table 2 reports the brokerage firms with the highest raw quantitative and qualitative beauty measures. Given that female analysts are consistently rated as more attractive than male analysts, we rank male and female analysts separately. To ensure the numbers reported are not driven by extreme observations, we consider only brokerage firms with at least 10 analyst photos, and we additionally require at least 3 female analyst photos for the female analyst ranking. The male analysts at Piper Jaffray and the female analysts at BofA Merrill Lynch received the highest ratings on average. While the higher average ratings for the analysts in some brokerage firms may be a coincidence, we do observe that some firms consistently employ good-looking analysts regardless of gender, such as UBS in our sample. We also observe that the rankings based on the quantitative and qualitative beauty measures are quite consistent.

4. Hypothesis Tests

4.1. Test of H1: Does a Beauty Premium Exist in the All-Star Analyst Voting?

4.1.1. Empirical Specification

The main research question of this study is whether beauty matters in the All-Star analyst voting process, and H1 asserts that there is no beauty premium in a highly competitive environment like All-Star analyst voting. To test this hypothesis, we regress analysts' All-Star award status on beauty, controlling for analysts' performance, brokerage firm resource and reputation, and the characteristics of the firms followed. As our observations are at the analyst-year level, for some control variables, we take the average of all firms in the analyst's research portfolio during the year. Specifically, we estimate the following probit model:

$$
\begin{aligned}
Star\_Award_{i,t} = \; & \beta_0 + \beta_1 \cdot Beauty_i + \beta_2 \cdot AFE_{i,t} + \beta_3 \cdot Horizon_{i,t} + \beta_4 \cdot Freq_{i,t} + \beta_5 \cdot BSize_{i,t} \\
& + \beta_6 \cdot NFirm_{i,t} + \beta_7 \cdot NInd_{i,t} + \beta_8 \cdot GExp_{i,t} + \beta_9 \cdot FExp_{i,t} + \beta_{10} \cdot Size_{i,t} \\
& + \beta_{11} \cdot MTB_{i,t} + \beta_{12} \cdot ROA_{i,t} + Industry\ Fixed\ Effects \\
& + Year\ Fixed\ Effects + \varepsilon_{i,t}\,, \qquad (1)
\end{aligned}
$$

where *Star_Award* denotes All-Star analyst award status, an indicator variable set to one if an analyst is ranked in the top three or is a runner-up by *Institutional Investor* in the analyst's respective industry in year t, and zero otherwise. *Beauty* denotes an analyst's facial attractiveness, measured as the average of the mean-adjusted quantitative scores received for each analyst, as explained in Section 3.

We control for analysts' performance by including their earnings forecasting activities, research portfolio complexity, and experience in the model. In particular, an analyst's earnings forecast error (*AFE*) is calculated as the analyst's average relative forecast error for the firms followed in year t, where the relative forecast error is the analyst's forecast error (i.e., the absolute difference between the analyst's earnings forecast and the firm's actual earnings) relative to the forecast errors of all analysts following the firm in year t and is standardized to range from 0 to 1 (Clement and Tse 2003). Earnings forecast horizon

(*Horizon*) is calculated as the analyst's average relative forecast horizon for the firms followed in year t, where the relative forecast horizon is the analyst's forecast horizon (i.e., the number of days between the analyst's initial earnings forecast and the firm's actual earnings announcement) relative to the forecast horizons of all analysts following the firm in year t, and is standardized to range from 0 to 1. Earnings forecast frequency (*Freq*) is calculated as the analyst's average forecast frequency for the firms followed in year t. The analyst's research portfolio complexity is measured by the number of firms followed (*NFirm*) and number of industries followed (*NInd*) in year t. The analyst's experience is measured by his or her general experience as an analyst (*GExp*) and the mean number of years that the analyst has followed the firms in the research portfolio (*FExp*) (Clement 1999). In addition, we control for brokerage firm resources and reputation by including brokerage firm size (*BSize*) in the model, measured by the number of analysts employed by the brokerage firm in year t. We further control for the characteristics of an average firm in the analyst's research portfolio in year t. These characteristics include: 1) average firm size (*Size*) measured as the mean of the natural logarithm of market value of the firms followed, 2) average market-to-book ratio of the firms followed (*MTB*), and 3) average return on assets of the firms followed (*ROA*) by the analyst in year t. These firm characteristics reflect analysts' coverage selection and to some extent the potential market impact of their equity research.

4.1.2. Results

Panel A of Table 3 presents descriptive statistics for the variables used in the empirical analysis. In our sample, approximately 8% of analysts were awarded All-Star status. Regarding the beauty measures, the average raw quantitative beauty measure is 49.07, whereas the average qualitative beauty measure is 2.14. Female analysts account for 9% of all analysts. On average, analysts cover 13 firms and

4 industries, and have 8.5 years of experience. The continuous variables are winsorized at the top and bottom 1%.

Panel B of Table 3 presents the correlations of the variables. While the All-Star analyst award status is significantly and positively correlated with female analysts, earnings forecasting activities, research portfolio complexity, experience, brokerage firm size, and the size and performance of the covered firms, it is not significantly correlated with analysts' facial attractiveness, consistent with H1 and the univariate result reported in Panel B of Table 2. Nevertheless, analysts' facial attractiveness is positively correlated with earnings forecasting activities such as accuracy and frequency and the performance of the covered firms, suggesting that good-looking analysts may be more capable. In addition, analysts' facial attractiveness is positively associated with female analysts and negatively associated with experience, which is correlated with age.[13]

Table 4 reports the results from the estimation of model (1), where standard errors are clustered at the brokerage firm level. In both columns 1 and 2, we find that the coefficient estimate on *Beauty* is statistically insignificant, suggesting that good-looking analysts do not benefit from their facial attractiveness in All-Star analyst voting. When *Beauty* is replaced by the raw quantitative or the qualitative beauty measures, we continue to find an insignificant coefficient on *Beauty*. These results are consistent with H1.

Although the prior literature suggests that physical attractiveness is correlated with many positive attributes such as ambitiousness, industriousness, confidence, popularity, and intelligence (Eagly et al.

[13] In an untabulated robustness check, we regress *Beauty* on the analyst's gender and general experience, and use the residual to proxy for the analyst's facial attractiveness. The inferences derived from the multivariate analysis remain unchanged.

1991; Feingold 1992), we do not observe a beauty premium in the professional, competitive financial analyst industry. The reason for this lack of a beauty premium is probably that the background and track record of each analyst's relative performance are readily available to voters, so they may place more weight on direct indicators of analysts' ability (e.g., research output) than indirect indicators (e.g., facial attractiveness). Turning to control variables, we document some determinants of All-Star analyst award status: analysts are more likely to be voted an All-Star when they issue more accurate and timelier forecasts, work for larger brokerage firms, have more firm experience, and follow more firms, fewer industries, and larger firms.

Overall, our results suggest that, on average, the beauty premium does not exist in the highly competitive environment of All-Star analyst voting and that the beauty premium found in some professional labor markets is not a universal phenomenon.

4.2. Test of H2: Does a Beauty Premium Exist Differentially for Male vs. Female Analysts?

4.2.1. Empirical Specification

H2 asserts that there is no interaction effect between beauty and gender on the likelihood of receiving All-Star analyst status, given the competitive and professional nature of the financial analyst industry. To test this hypothesis, we augment model (1) by including an indicator variable for gender and its interaction with *Beauty*. Specifically, we estimate the following probit model:

$$\begin{aligned} Star\_Award_{i,t} = \; & \beta_0 + \beta_1 \cdot Beauty_i + \beta_2 \cdot Female_i + \beta_3 \cdot Beauty_i * Female_i + \beta_4 \cdot AFE_{i,t} \\ & + \beta_5 \cdot Horizon_{i,t} + \beta_6 \cdot Freq_{i,t} + \beta_7 \cdot BSize_{i,t} + \beta_8 \cdot NFirm_{i,t} \\ & + \beta_9 \cdot NInd_{i,t} + \beta_{10} \cdot GExp_{i,t} + \beta_{11} \cdot FExp_{i,t} + \beta_{12} \cdot Size_{i,t} + \beta_{13} \cdot MTB_{i,t} \\ & + \beta_{14} \cdot ROA_{i,t} + Industry\ Fixed\ Effects + Year\ Fixed\ Effects + \varepsilon_{i,t}, \end{aligned} \tag{2}$$

where *Female* is an indicator variable set to one for female analysts, and zero otherwise. Other variables are as previously defined.

4.2.2. Results

Table 5 reports the results from the estimation of model (2). In both columns 1 and 2, we find that the coefficient estimate on *Beauty* remains statistically insignificant, suggesting that good-looking male analysts do not receive a beauty premium in All-Star analyst voting. The main effect of *Female* is significant and positive (β_3 = 0.292 and 0.363, z-statistic = 2.10 and 2.30, respectively), consistent with Kumar's (2010) finding that U.S. female analysts have better skills than male analysts due to self-selection. The marginal effect of *Female* in column 2 indicates that the probability of being voted as a star analyst is higher by 1.6%, which is an economically significant effect given that the average probability of being voted as a star analyst is 8% (Table 3, Panel A).

Perhaps surprisingly, in column 2, the coefficient estimate on the interaction of *Beauty* and *Female* is significant and negative (β_3 = -0.012, z-statistic = -2.14), suggesting that good-looking female analysts not only receive no benefit from their facial attractiveness but also are penalized in All-Star analyst voting. When the two alternative beauty measures are used, we continue to find similar significant interaction effects (p-value < 0.05 or better). As reported in Table 4, analyst forecast error is negatively associated with the likelihood of being voted an All-Star analyst. In addition, firm experience is a positive factor determining the likelihood of becoming an All-Star.

In sum, our results force us to reject H2 and furthermore suggest that the "dumb blonde" stereotype, a cognitive bias unique to some western cultures, manifests itself in the competitive and professional industry of financial analysts.

4.3. Test of H3: Does Information Asymmetry Affect the Beauty Premium?

4.3.1. Empirical Specification

To examine whether information asymmetry between analysts and fund managers concerning analysts' performance affects the beauty premium, we construct a composite index of industry-level information asymmetry based on a principal component analysis of the total number of analyst forecasts (i.e., the amount of analyst performance information), the dispersion of analyst forecasts (i.e., the uncertainty of analyst performance information), and the average firm experience of analysts (i.e., the track records of analyst performance) in an industry sector and year.[14] We then classify industries into high and low information asymmetry groups based on the median of this composite index. On average, the number of analyst forecasts in the high information asymmetry group is approximately 69% lower than in the low information asymmetry group, and the analyst forecast dispersion in the high information asymmetry group is 131% higher than in the low information asymmetry group.

To test H3, we augment model (2) by including an indicator variable for high information asymmetry and its interaction with *Beauty*. Specifically, we estimate the following probit model:

$$\begin{aligned} Star\_Award_{i,t} = \; & \beta_0 + \beta_1 \cdot Beauty_i + \beta_2 \cdot High\ Info\ Asymmetry_t \\ & + \beta_3 \cdot Beauty_i * High\ Info\ Asymmetry_t + \beta_4 \cdot Female_i \\ & + \beta_5 \cdot Beauty_i * Female_i + \beta_6 \cdot AFE_{i,t} + \beta_7 \cdot Horizon_{i,t} + \beta_8 \cdot Freq_{i,t} \\ & + \beta_9 \cdot BSize_{i,t} + \beta_{10} \cdot NFirm_{i,t} + \beta_{11} \cdot NInd_{i,t} + \beta_{12} \cdot GExp_{i,t} \\ & + \beta_{13} \cdot FExp_{i,t} + \beta_{14} \cdot Size_{i,t} + \beta_{15} \cdot MTB_{i,t} + \beta_{16} \cdot ROA_{i,t} \\ & + Industry\ Fixed\ Effects + Year\ Fixed\ Effects + \varepsilon_{i,t}, \end{aligned} \tag{3}$$

where *High Info Asymmetry* is an indicator variable set to one for industries classified as high information asymmetry, and zero otherwise. Other variables are as previously defined.

[14] The three variables load into two factors with eigenvalues greater than one, and the second factor is interpreted as information asymmetry about analyst performance. Specifically, the total number of analyst forecasts has a negative loading (coefficient = -0.555), the dispersion of analyst forecasts has a positive loading (coefficient = 0.832), and the average firm experience of analysts has a negative loading (coefficient = -0.011). As such, a higher value of the composite index suggests higher information asymmetry about analyst performance. The median value of the composite index is 0.076.

4.3.2. Results

Table 6 reports the results from the estimation of model (3). In both columns 1 and 2, we find that while the coefficient estimate on *Beauty* is insignificant, the interaction of *Beauty* and *High Info Asymmetry* is significant and positive (β_3 = 0.09 and 0.012, z-statistic = 2.01 and 2.09, respectively). The combined effects of *Beauty* and *Beauty***High Info Asymmetry* are statistically different from zero (p-value < 0.1 or better), suggesting that good-looking male analysts in an environment with high information asymmetry receive a beauty premium in the voting. In terms of economic significance, in column 2, a one-standard-deviation increase in *Beauty* for male analysts in high information asymmetry industry sectors would lead to a 4% increase in the current probability of being voted as a star analyst.

In untabulated tests, instead of using the composite index, we use (1) the number of analysts, (2) the number of analyst earnings forecasts, (3) the number of analyst recommendations, and (4) both the number of analyst earnings forecasts and the number of analyst recommendations in an industry and year to proxy for information asymmetry. With these alternative classifications, we continue to find a significant beauty premium for good-looking male analysts in industry sectors with high information asymmetry. Collectively, our findings lend support to the conjecture that low information asymmetry reduces the beauty premium for male analysts.

5. Additional Tests

5.1 Beauty Premium and Analyst Visibility

An alternative explanation for the lack of a beauty premium can be due to the visibility of financial analysts.[15] If fund managers never meet analysts in person or see their pictures, beauty should have little effect on voting outcomes. To test this alternative explanation, we investigate whether the beauty premium varies with physical distance between analysts and fund managers or with media

[15] Eckel and Petrie (2011) find that people are willing to pay extra to see or have face-to-face interaction with peers, suggesting that facial cues have informational value.

coverage of analysts. Specifically, regarding physical distance, we assume analysts working in New York City (*NYC*), where the major stock exchanges are located, have more opportunities for face-to-face interaction with voters; as for media coverage, we calculate the number of times an analyst appears in major news and business sources (*MCover*), such as press release wires, Reuters newswires, and the *Wall Street Journal*. We then add *NYC* and *MCover* and their interactions with *Beauty* to Model (2) and re-estimate the regression.[16]

The untabulated results show that the coefficient estimates on *NYC* and *MCover* are positive and significant, but do not change the significance of *Beauty* and the interaction term *Beauty*Female*. In addition, the interaction terms *Beauty*NYC* and *Beauty*MCover* are positive but insignificant. These results suggest that the visibility of analysts affects the likelihood of All-Star awards, but has little effect on the influence of the beauty premium in All-Star analyst voting. Taken together, our evidence does not support the conjecture that the visibility of analysts explains the absence of a beauty premium in All-Star analyst voting.

5.2 Beauty Premium and Analyst Performance

As previously discussed, beauty may be used as an indirect measure for unobservable skills or ability (e.g., Mobius and Rosenblat 2006). Therefore, a natural question would be whether more physically attractive analysts are also better performers. To answer this question, we use analysts' average relative earnings forecast error (*AFE*) to proxy for their performance and examine its relationship with *Beauty*.[17] Specifically, we regress analysts' average relative earnings forecast error on *Beauty* and control

[16] The locations of the U.S. analysts are extracted from their LinkedIn pages.
[17] We multiply analyst earnings forecast error (*AFE*) by 100 to make the coefficient estimates more readable.

for forecast horizon, forecast frequency, brokerage firm size, research portfolio complexity, experience, and average firm characteristics in the analysts' research portfolios, where *Beauty* is measured based on the raw quantitative, mean-adjusted quantitative, or raw qualitative beauty scores.

Table 7 reports the regression results based on the mean-adjusted quantitative beauty measure. In columns 1 and 2, we find that the coefficient estimate on *Beauty* is negative and significant (β_1 = -0.034 and -0.014, t-statistic = -3.52 and -1.75, respectively), suggesting that good-looking analysts are better forecasters. In column 3, when we interact *Beauty* and *Female* in the above regression, we find a negative main effect on *Beauty* (β_1 = -0.018, t-statistic = -2.51), but insignificant effects on *Female* and *Beauty***Female*. In terms of economic significance, a one-standard-deviation increase in *Beauty* in column 3 is associated with a 1% decrease in *AFE* relative to the mean *AFE* in our sample. These findings are consistent with physical attractiveness being an indirect measure of analyst performance. However, the insignificant interaction effect of *Beauty* and *Female* suggests that beauty has no effect on the association between forecast performance and gender, and thus the beauty penalty on pretty female analysts found in All-Star analyst voting is likely a behavioral bias.

6. Conclusion

This paper investigates whether a beauty premium exists in All-Star analyst voting. Collectively, we find that beauty, on average, does not affect the likelihood of being voted as an All-Star analyst. However, a beauty premium emerges when information asymmetry about analyst performance is high. The evidence supports the conjecture that a major reason for the beauty premium is decision makers not having enough information to assess a subject's performance and thus placing some weight on beauty as an indirect indicator of the subject's ability. Once information becomes transparent, the premium decreases or disappears. This finding therefore implies that the beauty premium, a commonly posited behavior bias, can be mitigated by a strong economic force.

The fact that female U.S. analysts are more likely to be voted as All-Star analysts supports the assertion that the small number of female analysts (only 8%) who stay in the profession are very competent and competitive. However, our finding also shows that attractive female U.S. analysts receive a "beauty penalty" consistent with the common "dumb blonde" stereotype. Our findings therefore suggest that the gender effect can manifest itself distinctively.

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Table 1
Sample Selection

Sample selection criteria	Number of Observations
Analysts with names in the I/B/E/S recommendation file, 2014–2015	4,377
Exclude: without LinkedIn profile	(1,755)
Exclude: without quality photos for rating	(1,195)
	1,427
Analyst-years with quality photos and EPS forecasts, 2013–2015	3,695
Exclude: industries not classified by *Institutional Investor* magazine	(614)
Exclude: without actual EPS to calculate EPS forecast errors	(13)
Exclude: without financial statement data to calculate control variables	(215)
Exclude: without any All-Star analyst in an industry-year	(81)
Final sample: number of analyst-years (analysts)	2,772 (1,135)

This table presents the sample selection criteria. We start with a sample of 1,427 U.S. analysts with quality photos for rating purposes. After merging with I/B/E/S and Compustat databases, we derive the final sample consisting of 2,772 U.S. analyst-years for the years 2013 to 2015.

Table 2
Summary Statistics for Beauty Measures

Panel A: MTurk vs. student ratings

	Quantitative			Qualitative		
	Mean	Med	Stdev	Mean	Med	Stdev
MTurk ratings	49.56	50.00	20.98	2.16	2.00	0.79
Student ratings	43.55	45.00	21.38	1.88	2.00	0.74

Panel B: Means by analyst grouping

	Quantitative	Qualitative
By gender:		
Male analysts	48.32	2.11
Female analysts	60.20	2.57
Difference: male – female	-11.88***	-0.46***
By award status:		
Star analysts	49.04	2.12
Non-Star analysts	49.39	2.15
Difference: Star – non-Star	-0.35	-0.03

*, **, and ***, indicate significance of mean difference at the 10%, 5%, and 1% levels, respectively.

Panel C: Means by brokerage firm

	Quantitative (Number of analysts)	Qualitative
Male Top 5:		
Piper Jaffray	54.33 (13)	2.32
Robert W. Baird & Co.	52.77 (15)	2.29
Citigroup	52.47 (17)	2.25
J.P. Morgan	51.44 (21)	2.25
UBS (U.S.)	51.37 (25)	2.15
Female Top 5:		
BofA Merrill Lynch	66.59 (8)	2.85
Stifel Nicolaus	64.76 (3)	2.76
UBS (U.S.)	63.50 (5)	2.65
Credit Sussie First Boston	63.45 (5)	2.75
Barclays Capital	62.85 (6)	2.67

This table reports the summary statistics of the raw quantitative and qualitative beauty measures by raters (Panel A), by analyst groupings (Panel B), and by brokerage firms (Panel C). To reduce the impact of extreme values, in Panel C, we only consider brokerage firms with at least ten analysts with valid photos; for female analyst rankings, we additionally require at least three female analysts with valid photos.

Table 3
Summary Statistics for Key Variables

Panel A: Descriptive statistics

	(N = 2,772)		
Variable	Mean	Median	Stdev
Star_Award	0.08	0.00	0.28
Beauty (Quantitative)	49.07	48.54	10.85
Beauty (Qualitative)	2.14	2.11	0.44
Beauty (Mean-Adj. Quantitative)	-2.31	-1.19	17.91
Female	0.09	0.00	0.29
AFE	0.29	0.26	0.15
Horizon	0.75	0.78	0.17
Freq	3.99	3.75	1.76
BSize	60.69	42.38	55.94
NFirm	13.35	13.00	7.05
NInd	4.22	4.00	2.46
GExp	8.46	7.50	6.67
FExp	4.18	3.61	2.45
Size	8.89	8.96	1.45
MTB	5.71	3.89	7.12
ROA	0.00	0.03	0.12

Panel B: Correlation table

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) *Star_Award*	1												
(2) *Beauty*	-0.01	1											
(3) *Female*	**0.04**	**0.22**	1										
(4) *AFE*	**-0.10**	**-0.03**	0.01	1									
(5) *Horizon*	**0.16**	-0.01	-0.01	**0.10**	1								
(6) *Freq*	**0.17**	**0.07**	**0.05**	**-0.21**	**0.38**	1							
(7) *BSize*	**0.28**	**0.04**	**0.10**	**-0.04**	**0.08**	**0.16**	1						
(8) *NFirm*	**0.24**	**-0.05**	**-0.09**	**-0.07**	**0.23**	**0.15**	**0.09**	1					
(9) *NInd*	0.02	**-0.05**	**-0.08**	**0.07**	**0.09**	**-0.08**	**-0.06**	**0.44**	1				
(10) *GExp*	**0.14**	**-0.17**	**-0.06**	**0.05**	**0.22**	**-0.05**	**-0.08**	**0.29**	**0.19**	1			
(11) *FExp*	**0.22**	**-0.11**	-0.02	**0.07**	**0.39**	**0.13**	-0.02	**0.23**	**0.10**	**0.69**	1		
(12) *Size*	**0.20**	0.00	-0.02	**-0.23**	**0.26**	**0.16**	**0.14**	**0.09**	**-0.09**	**0.16**	**0.24**	1	
(13) *MTB*	0.01	0.03	**0.07**	-0.01	0.01	**-0.08**	0.00	**0.04**	-0.00	0.01	-0.03	**0.06**	1
(14) *ROA*	**0.07**	**0.04**	0.02	-0.03	**0.10**	**0.07**	**0.13**	**-0.05**	0.02	**0.04**	**0.17**	**0.39**	**-0.09**

Boldface indicates significance at the 10% level.

Panel A of this table presents descriptive statistics for the sample used in the empirical tests. Panel B presents the correlations of the key variables. *Star_Award* = All-Star analyst, an indicator variable set to one if the analyst is an All-Star analyst in year t, and zero otherwise. *Beauty* = facial attractiveness of the analyst, measured in raw quantitative, qualitative, and mean-adjusted quantitative terms. *Female* = an indicator variable set to one if the analyst is female, and zero otherwise. *AFE* = earnings forecast error, calculated as the analyst's average relative forecast error for the firms followed in year t, where the relative forecast error is the analyst's forecast error (i.e., the absolute difference between the analyst's earnings forecast and the firm's actual earnings) relative to the forecast errors of all analysts following the firm in year t and is standardized to range from 0 to 1. *Horizon* = earnings forecast horizon, calculated as the analyst's average relative forecast horizon for the firms followed in year t, where the relative forecast horizon is the analyst's forecast horizon (i.e., the number of days between the analyst's initial earnings forecast and the firm's actual earnings announcement) relative to the forecast horizons of all analysts following the firm in year t, and is standardized to range from 0 to 1. *Freq* = earnings forecast frequency, calculated as the analyst's average relative forecast frequency for the firms followed in year t; the relative forecast frequency is the analyst's forecast frequency relative to the forecast frequencies of all analysts following the firm in year t. *BSize* = brokerage firm size, calculated as the number of analysts employed by the sell-side firm in year t. *NFirm* = number of firms followed by the analyst in year t. *NInd* = number of industries followed by the analyst in year t. *GExp* = general experience, defined as the number of years between an analyst's first appearance in the I/B/E/S database and the end of year t. *FExp* = firm-specific experience, defined as the average number of years that the analyst has followed the firms in his or her research portfolio in year t. *Size* = average firm size, measured as the mean of the natural logarithm of market value of the firms followed by the analyst in year t. *MTB* = average market-to-book ratio of the firms followed by the analyst in year t. *ROA* = average return on assets of the firms followed by the analyst in year t.

Table 4
Test of H1: Does a Beauty Premium Exist in All-Star Analyst Voting?

	(1)	(2)
	Star_Award	*Star_Award*
Beauty	-0.001	-0.002
	(-0.72)	(-0.96)
AFE		-1.987***
		(-2.86)
Horizon		1.185**
		(2.08)
Freq		0.049
		(1.42)
BSize		0.008***
		(6.50)
NFirm		0.074***
		(3.96)
NInd		-0.074**
		(-2.14)
GExp		-0.008
		(-0.44)
FExp		0.122***
		(4.13)
Size		0.384***
		(5.49)
MTB		0.004
		(1.11)
ROA		0.432
		(0.38)
Industry Fixed Effects	Included	Included
Year Fixed Effects	Included	Included
N	2,772	2,772
Pseudo R-squared	0.026	0.363

This table presents the results from estimating the probit regression of Model (1). *Star_Award* = All-Star analyst, an indicator variable set to one if the analyst is an All-Star analyst in year t, and zero otherwise. *Beauty* = facial attractiveness of the analyst, measured based on the mean-adjusted quantitative scores for the analyst. All other variables are as previously defined. *z*-statistics (in parentheses) are calculated based on standard errors clustered at the broker level. *, **, and ***, indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 5
Test of H2: Does a Beauty Premium Exist Differentially for Male vs. Female Analysts in All-Star Analyst Voting?

	(1)	(2)
	Star_Award	*Star_Award*
Beauty	-0.002	-0.002
	(-0.89)	(-0.64)
Female	0.292**	0.363**
	(2.10)	(2.30)
*Beauty * Female*	-0.002	-0.012**
	(-0.42)	(-2.14)
AFE		-1.997***
		(-2.93)
Horizon		1.220**
		(2.15)
Freq		0.045
		(1.25)
BSize		0.008***
		(6.61)
NFirm		0.076***
		(4.01)
NInd		-0.072**
		(-2.11)
GExp		-0.011
		(-0.64)
FExp		0.125***
		(4.55)
Size		0.390***
		(5.45)
MTB		0.004
		(0.90)
ROA		0.511
		(0.46)
Industry Fixed Effects	Included	Included
Year Fixed Effects	Included	Included
N	2,772	2,772
Pseudo R-squared	0.030	0.367

This table presents the results from estimating the probit regression of Model (2). *Star_Award* = All-Star analyst, an indicator variable set to one if the analyst is ranked as an All-Star analyst in year t, and zero otherwise. *Beauty* = facial attractiveness of the analyst, measured based on the mean-adjusted quantitative scores for the analyst. *Female* = an indicator variable set to one if the analyst is female, and zero otherwise. All other variables are as previously defined. *z*-statistics (in parentheses) are calculated based on standard errors clustered at the broker level. *, **, and ***, indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 6
Test of H3: Does Information Asymmetry Affect the Beauty Premium?

	(1)	(2)
	Star_Award	*Star_Award*
Beauty	-0.005	-0.006
	(-1.35)	(-1.56)
High Info Asymmetry	0.005	0.213
	(0.02)	(1.12)
*Beauty * High Info Asymmetry*	0.009**	0.012**
	(2.01)	(2.09)
Female		0.332**
		(1.96)
*Beauty * Female*		-0.014***
		(-2.72)
AFE		-1.951***
		(-2.78)
Horizon		1.120*
		(1.83)
Freq		0.462
		(1.13)
BSize		0.007***
		(6.69)
NFirm		0.075***
		(3.86)
NInd		-0.083**
		(-2.22)
GExp		0.107***
		(4.08)
FExp		0.396***
		(5.68)
Size		0.003
		(0.96)
MTB		0.619
		(0.56)
ROA		-0.006
		(-1.56)
Industry Fixed Effects	Included	Included
Year Fixed Effects	Included	Included
N	2,772	2,772
Pseudo R-squared	0.030	0.370

This table presents the results from estimating the probit regression of Model (3) on the high vs. low industry-level information asymmetry subsamples. *Star_Award* = All-Star analyst, an indicator variable set to one if the analyst is ranked as an All-Star analyst in year t, and zero otherwise. *Beauty* = facial attractiveness of the analyst, measured based on the mean-adjusted quantitative scores for the analyst. *High Info Asymmetry* = an indicator variable set to one if the industry is classified as high information asymmetry, and zero otherwise. All other variables are as previously defined. *z*-statistics (in parentheses) are calculated based on standard errors clustered at the broker level. *, **, and ***, indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 7
Analyst Beauty and Performance

	(1)	(2)	(3)
	AFE	*AFE*	*AFE*
Beauty	-0.034***	-0.014*	-0.018**
	(3.52)	(-1.75)	(-2.51)
Female			0.396
			(0.42)
*Beauty * Female*			0.020
			(0.53)
Horizon		39.400***	39.414***
		(38.52)	(38.79)
Freq		-0.238***	-0.242***
		(-2.60)	(-2.61)
BSize		0.008	0.008
		(1.30)	(1.23)
NFirm		-0.202***	-0.200***
		(-4.94)	(-5.03)
NInd		0.357**	0.357**
		(2.25)	(2.18)
GExp		-0.057**	-0.056**
		(-2.39)	(-2.33)
FExp		0.185	0.184
		(1.46)	(1.46)
Size		-1.625***	-1.622***
		(-4.45)	(-4.35)
MTB		-0.012	-0.014
		(-0.69)	(-0.89)
ROA		2.468	2.419
		(0.58)	(0.57)
Industry Fixed Effects	Included	Included	Included
Year Fixed Effects	Included	Included	Included
N	2,772	2,772	2,772
Adj. R-squared	0.045	0.386	0.386

This table presents the results from estimating the OLS regression of analyst performance on beauty. *AFE* = earnings forecast error, calculated as the analyst's average relative forecast error for the firms followed in year t, where the relative forecast error is the analyst's forecast error relative to the forecast errors of all analysts following the firm in year t and is standardized to range from 0 to 1. *Beauty* = facial attractiveness of the analyst, measured based on the mean-adjusted quantitative scores for the analyst. All other variables are as previously defined. *t*-statistics (in parentheses) are calculated based on standard errors clustered at the broker level. *, **, and ***, indicate significance at the 10%, 5%, and 1% levels, respectively.