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More than Skin-deep? Analysts' Beauty and Their Performance

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Abstract

Prior research finds that an analyst's job performance such as forecast accuracy and informativeness of stock recommendations is affected by various acquired attributes such as education level, experience, resources, and social networks. We show in this paper that an ascriptive feature of an analyst's, namely her beauty level, also has a significant impact on her performance. We find that analysts with a higher beauty level make more accurate forecasts and more informative stock recommendations. Such superior job performance at least partially derives from their privileged information access with management. Further evidence indicates that such a privilege at least partially stems from managers' indulgence of their tastes for beauty, especially when they are less concerned about their firms' stock performance and hence the analysts' abilities. Finally, beauty also affects analysts' career opportunities: They are more likely to be nominated to a higher place in the star-analyst list and more likely to be hired by a large brokerage from a smaller one.

I. Introduction

This study examines the potential impact of beauty, or physical attractiveness on the performance of sell-side financial analysts. A long line of research has documented the existence of beauty premium, where good-looking individuals obtain more job opportunities and higher salaries than average-looking individuals (Hamermesh and Biddle 1994, Fletcher 2009, Harper 2000, etc). Subsequent research finds evidence of the beauty premium in specific careers such as legal services, politics, sales and advertising, etc., that involve frequent communications and interactions with customers or voters. Researchers use laboratory experiments to investigate the potential sources of the beauty premium. While some document evidence of employer discrimination (Rooth 2009, Senior et al. 2007, Boo et al. 2013, Ruffle and Shtudiner 2015), others find that more attractive individuals are more successful in various types of transactions, suggesting that they may be able to add value to their employers by making better deals with clients (Mulford et al. 1998, Solnick and Schweitzer 1999, Landry et al. 2006, Andreoni and Ragan 2008, Belot 2012). In contrast to the long line of experimental research, empirical evidence on the beauty premium in the real-life business context is scarce. While Pfann et al. (2000) find that beauty helps executives of advertising agencies to gain greater revenue this evidence is limited to a specific industry where beauty is likely to matter.

In the current study, we examine whether beauty matters to business professionals in the sell-side financial analyst industry. We focus on financial analysts for two reasons. First, laboratory experiments identify direct communication and interaction as critical condition for beauty to have an impact. In addition, the interaction is “asymmetric” in the sense that one party takes the position to allocate resources to the other party and has substantial discretion in deciding how much the other party will receive. The sell-side financial analysts industry provides an ideal setting to examine the beauty effect because financial analysts communicate regularly with firm management to obtain firm-specific information. In addition, management has substantial discretion in deciding to whom such private information is provided, if any.

Second, one difficulty of using empirical data to examine employee productivity is to find a clean measure of individual productivity or performance. In the case of CEOs, researchers often use firm performance as a proxy, but this measure is very noisy and suffers severe endogeneity. As a comparison, the performance of financial analysts can be directly measured by the quality of their earnings forecast and stock recommendations, and prior research suggests that this quality is significantly affected by analysts' access to private information through management (Green et al. 2014, Brown et al. 2015). Therefore, if we observe an association between physical attractiveness of financial analysts and the quality of their forecasts and recommendations it is reasonable to infer that beauty plays a role by affecting the information acquisition activity of the analysts.

Our study makes several contributions to the beauty premium literature and to the financial analysts literature. First, prior research on beauty premium covers either the labor markets in general (Hamermesh and Biddle and 1994, Fletcher 2009, Harper 2000) or specific industries such as advertising where appearance obviously matters (Pfann et al. 2000). Our study is the first to document a significant impact of beauty on a group of business professionals, namely sell-side financial analysts. This evidence updates our knowledge of the scope of the beauty effect and refutes the traditional view that beauty does not matter to business professionals due to the high-skill nature of their jobs.

Second, because financial analysts are a key player in the capital market and their work influences market efficiency, capital allocation, and stock liquidity, our evidence suggests that beauty influences the functioning of the capital market by affecting the acquisition and dissemination of firm-specific information.

Third, prior research uses laboratory experiments to identify circumstances where beauty may affect the outcome of a deal. The experiments are designed to capture real-world activities that involve negotiation, bargaining, and soliciting. However, real-world evidence on how exactly beauty adds value to employers is scarce. To our knowledge, this study is the first to use empirical data to identify a specific channel through which beauty creates value. Specifically, we find that attractive financial analysts create value to their brokerage house by producing more accurate earnings forecasts and more informative stock recommendations because they are able to obtain more private information from corporate executives. The effect of beauty on information acquisition has never been identified in the prior literature.

Fourth and related to above, one justification of the beauty premium is that attractive employees are paid more because they are more successful in dealing with clients. However, even if that is the case it is still an open question whether customer preference is taste-based or justified by the higher quality and productivity of attractive workers. For example, Biddle and Hamermesh (1998) find evidence of self-sorting and beauty premium among attorneys, but they cannot identify whether better looking attorneys in private sectors (where attorneys work for clients) are indeed more helpful to their clients (for example, winning more cases) than plain-looking attorneys. Our study finds evidence that firm managers become less discriminating to financial analysts when they are more dependent on their work, indicating that managers' favorable treatment to attractive analysts are driven by their taste rather than by their belief of higher quality of attractive analysts. This finding helps researchers to obtain a deeper understanding of the sources of the beauty premium in real world.

Finally, our study contributes to the financial analyst literature by identifying an ascriptive analyst characteristic that influences analysts' performance. Prior studies have identified various determinants of analyst performance such as economic incentives and career concerns. A few studies examine the impacts of social characteristics such as gender (Green et al. 2009, Kumar 2010, Li et al. 2013) and social networks (Cohen et al. 2010), which have long been found to influence individual behaviors in social contexts in sociology and phycology. We add to this line of research by documenting the performance effect of another factor, physical attractiveness that has been documented to have wide impacts on the labor markets but has never been explored for the sell-side financial analyst industry.

II. Literature and the hypothesis

Beauty premium

Prior research has documented a beauty premium in the labor markets where attractive people are more successful in obtaining jobs and earn higher salaries than average-looking people. For example, on the basis of household survey from the U.S. and Canada, Hamermesh and Biddle (1994) show that good-looking people earn about 12-14% more than plain-looking people. Fletcher (2009) confirms the beauty premium using more recent U.S. data. Harper (2000) documents strong plainness penalty and weak beauty premium in the U.K. Subsequent studies find that beauty provides an advantage to individuals in professions that involve social interactions such as lawyers (Biddle and Hamermesh 1998), politicians in electoral campaigns (Benjamin et al. 2009, Leigh and Susilo 2009, Berggren et al 2010), and MBAs in their employment upon graduation and also in their long-term employment (Frieze et al. 1991). For example, Biddle and Hamermesh (1998) find that better-looking attorneys self-sort into private sectors (where the attorneys work for clients) while plain-looking attorneys self-sort into public sectors (where the attorneys work for government as prosecutors, staff attorneys, etc.). They also find that the beauty premium in the private sector is greater than that in the public sector over the long run.

Given the robust evidence of beauty premium in the labor markets, one natural question to ask is whether the beauty premium is driven by employer discrimination or enhanced productivity associated with beauty.[1] Researchers use laboratory experiments to document evidence consistent with employer discrimination: more attractive individuals are more likely to have job opportunities with the same qualifications as the control group (Rooth 2009, Boo et al. 2013, Ruffle and Shtudiner 2014). In addition, Mobius and Rosenblat (2006) use an experiment to disentangle the sources of the beauty premium. They find that the beauty premium comes from three sources: perceived greater capability of more attractive employees by the employer (even though they do not perform better than others), greater confidence level of attractive employees, and better communication skills of attractive employees. These findings suggest that employer discrimination can be unintentional or unconscious. Consistent with Mobius and Rosenblat (2006), Deryugina and Shurchkov (2015) find that the beauty premium exists in a bargaining task (where communication skills are important) but not in an analytical task or a data entry task.

In addition to documenting the existence of the beauty premium, experimental researchers also demonstrate that more attractive individuals can be more successful in circumstances other than employment. For example, Mulford et al. (1998) find that experiment participants are more likely to enter a game with attractive people, and once in the game they are

[1] The enhanced productivity is defined from the employer's perspective; that is, whether more attractive employees can bring more business to the employer. The greater productivity can still be due to customer's bias either intentional or unintentional.

more cooperative and also expect attractive people to be more cooperative. Solnick and Schweitzer (1999) find that in an ultimatum game that captures the bargaining process attractive people were offered more money and were also demanded for more, consistent with people are more generous to and more demanding of attractive individuals. Andreoni and Ragan (2008) find that attractive individuals earn more contributions in a public-good game because they are expected to be less selfish even though this is not the case. Furthermore, Belot et al. (2012) find that unattractive contestants are more likely to be eliminated by their peers in games even though they are equally cooperative and their performance is no worse. Finally, using door-to-door fund-raising field experiment, Landry et al. (2006) show that attractiveness of female solicitor can increase donations significantly. Overall, these studies suggest that more attractive individuals receive better treatment in deals which allows them to gain economic benefits. If we view experiment subjects as potential employees and customers the above findings in effect support the argument of "enhanced productivity" in explaining the beauty premium. That is, attractive employees may create more value to their employers than unattractive employees due to their superior deal-making ability, and being aware of this, employers pay more to attractive employees.

Empirical research on beauty premium and its sources for business professionals was scarce until very recently. Pfann et al. (2000) find that more attractive executives of Dutch advertising firms generate higher revenues for their firms, which far exceed the likely extra salaries that the executives command. However, the results and inferences are limited to one industry where appearance matters significantly.

For financial analysts, the type of their interactions in the information acquisition process is specific: they interact with firm managers to obtain firm-specific information, which influences the quality of their subsequent earnings forecasts and stock recommendations. Thus, the setting allows us to identify the effect of beauty in a direct way; that is, it allows us to explore how beauty affects one's ability to acquire valuable private information from another party, which has not been explored in prior research and would be difficult to observe for corporate executives due to the large varieties of their daily communications.

<u>Financial analysts</u>

Prior studies have identified various factors that influence analyst forecasting behavior and performance such as economic incentives, analysts' career and reputational concerns, and behavioral bias (see Mehran et al. 2007, Ramnath et al. 2008 for surveys of this research). A few recent studies examine the impacts of personal characteristics such as gender and social networks (Cohen et al. 2010; Kumar, 2010; Green et al. 2009). We add to this line of research by considering an ascriptive factor, i.e., physical attractiveness , that is likely to influence financial analysts' performance based on research in sociology, phycology and economics.

Hypothesis

Prior evidence of the beauty premium either comes from a nation's entire labor markets (Hamermesh and Biddle and 1994, Fletcher 2009, Harper 2000) or from specific industries where beauty is likely to have a significant impact (Pfann et al. 2000), but a few studies suggest that beauty premium may also exist in high-skill professions such as financial analysts. For example, in a laboratory experiment that requires experienced personnel interviewers to evaluate job applicants, Waters (1985) find that physical appearance plays an important role in the hiring process for all types of jobs, but the beauty premium is greater for low skill jobs (secretary) than for high-skill jobs (financial analyst). [2] In addition, Biddle and Hamermesh (1998) find beauty premium in the legal profession, where professional skills and experience should be critical to success. The authors conjecture that the beauty premium is likely to be driven by clients' preference of dealing with more attractive attorneys. Sell-side financial analysts face a similar situation in that their performance is largely influenced by the treatment that they receive from firm management in information sharing. Finally, anecdotal evidence suggests that practitioners in the finance industry also acknowledge the importance of looks.[3]

We argue that beauty has the potential to influence the performance of financial analysts because their performance relies heavily on the outcome of their communication with firm managers. Research suggests that access to private information is key determinant of the accuracy and informativeness of analyst earnings forecasts and stock recommendations. For example, Green et al. (2014) find that changes in analysts' stock recommendation receive a greater market reaction when analysts' brokerage hosts investor conferences during which analysts have access to firm management. In addition, analysts at conference-hosting brokerages produce more informative, accurate and timely earnings forecasts. Using actual record of private communication with financial analysts of a large-cap NYSE-traded firm, Soltes (2014) finds that 16 of all 27 analysts (60%) following the firm had private communication with the firm during the sample year, with a total number of 75 (an average of 4.7 for those that communicate). In addition, the accuracy of forecast revisions increases after private communication for a subsample of analysts that update their forecasts soon after the private communication. Finally, a

[2] Another related study is Frieze et al. (1991), who finds that more attractive MBA students earn higher salaries upon graduation and in ten years after graduation. To the extent that MBAs work at management positions the evidence supports the role of beauty premium in high-skilled jobs.

[3] See, for example, http://www.wallstreetoasis.com/forums/does-appearance-matter-for-men, http://www.streetofwalls.com/finance-training-courses/investment-banking-overview-and-behavioral-training/investment-banking-job-interview/;

survey by Brown et al. (2015) reveals that around 66% (72%) of sell-side financial analysts view private communication with management as very useful to their earnings forecasts (stock recommendations), second only to the level of the analyst's industry knowledge.[4]

Importantly, prior research also documents that firm management discriminates among financial analysts in determining the amount of private information to be provided. For example, many studies provide evidence consistent with managers disclosing more information to financial analysts that provide favorable earnings forecasts or stock recommendations (Chen and Matsumoto 2006, Ke and Yu 2006, Mayew 2008, etc.). [5] Cohen et al (2010) identify another factor that leads to management discrimination in information sharing but is less likely driven by managers' financial incentives. Specifically, Cohen et al. (2010) find that analysts that have school ties with the firm's managers issue more profitable stock recommendations presumably because managers provide more information to connected financial analysts, a behavior consistent with the long-documented social networks effect where social ties facilitate information transmission among connected individuals. Importantly, there is no obvious evidence that managers benefit from this information sharing, suggesting that non-financial incentives can also motivate managers to share information. In a similar vein, it is possible that firm managers discriminate among financial analysts due to their personal tastes such that they are more willing to share information with financial analysts that are more physically attractive.

Finally, it is also possible that the discrimination of firm managers is unconscious if they perceive attractive analysts as more competent (even though this is not the truth) or if more attractive analysts possess superior social and communication skills. These possibilities are

[4] In the case of stock recommendation, the importance of private communication to management is ranked No. 3, following industry knowledge and the analyst's own earnings forecast.

[5] Consistent with these studies, Brown et al. (2015) reveal that around one quarter of analysts surveyed indicate that they are very likely to lose access to management if they issue unfavorable stock recommendations, while only 18% indicated this is very unlikely.

consistent findings of the sources of the beauty premium in Mobius and Rosenblat (2006). Overall, the above discussions suggest a positive association between physical attractiveness of financial analysts and the quality of their earnings forecasts. On the other hand, the financial analyst industry is highly professional where skills and experience should matter the most, and physical appearance should play a much smaller role.

In addition, the critical role that financial analysts play to firms may also curb the potential discriminating behavior of managers. Research shows that analyst forecast coverage stimulates investor interest and improves liquidity (Merton 1987, Irvine 2003 Roulstone 2003, Li and You 2015), and helps firms to lower cost of capital (Frankel and Li 2004). Research also finds that firms lose significant benefits when analyst coverage drops. For example, using broker downsizing to identify exogenous changes in analyst coverage, researchers find that decrease in analyst coverage leads to increased information asymmetry and cost of capital (Kelly and Ljungqvist 2012, Derrien and Kecskes 2013) and as a result, firms reduce their investment and financing (Derrien and Kecskes 2013), and firms respond to the loss of analyst coverage by increasing voluntary disclosures which incur nontrivial costs (Anantharaman and Zhang 2011). We observe that firms affected by the brokerage mergers and closures lose only one analyst in general,[6] indicating the nontrivial value of each individual analyst. Therefore, to the extent that managers are fully aware of the importance of financial analysts, we expect managers to refrain themselves from exerting significant taste-driven discrimination.

Overall, it is an empirical question whether physical attractiveness of financial analysts matters to their performance. Using analyst earnings forecast errors to proxy for their performance, we make the following hypothesis:

Hypothesis 1: Financial analysts' beauty level are negatively associated with their earnings

[6] See, for example, Derrien and Kecskes (2013, Figure 1), Chen et al. (2015, Tables 1, 5, 8).

forecast errors.

III. Sample and data

Sample

Our sample of analysts comprises those who had registered with the Securities Association of China (SAC) by the end of Dec 31, 2011 and who are also covered by the CSMAR analyst forecasts database. The sample period runs from 2005 to 2014.

Table 1 shows that the number of analysts in our sample varies from 408 (in 2005) to 1,571 (in 2010). Although the population of Chinese analysts is more than 2,000 in later years of our sample period and CSMAR obviously only cover a portion of them, we note that these analysts are those employed by relatively large brokerages and their research reports in general bear a larger influence in the market. Considering that the number of unique brokerages in the Chinese population is seldom over 100, our sample based on CSMAR in most years includes the majority of these brokerages. The relative comprehensiveness of our sample is also evident for the stocks with non-zero analyst following.

Rating of beauty

We download head-to-shoulder ID photos of 2,630 sell-side financial analysts from the website of Securities Association of China (http://zg.sac.net.cn/publicmain). Then we randomly sort the photos into four lists. Each rater is randomly assigned one of the four lists for rating. By this design we reduce the likelihood that photos appearing earlier in the rating process are treated differently as compared to those appearing later due to fatigue or boredom across raters. Next, we divide each list into five parts with each consisting of about 500 analysts. We send the five parts separately to the rater. Only after the rater returns the rating results of the previous part do we send the following part. The purpose is to control the rating speed and also avoid the raters' attention exhaustion.

In the rating process, each rater only sees the alpha-numeric ID, not the corresponding analyst's real name, of each photo (e.g., a0001, …, a2,630) in a Microsoft Excel rating sheet. Individual analysts' photos named using each analyst's photo ID are contained in a folder. The raters are instructed to use the Windows Photo Viewer to view the photo and give the beauty score for each analyst.

To maintain the raters' alertness in matching the photo in the folder with the analyst ID in the excel sheet through the rating process, we randomly add two empty IDs that do not match with any analyst's photo in the excel sheet. We should not observe any ratings for these two IDs.

Each photo can have one of five ratings: 5 for strikingly beautiful/handsome, 4 for above average, 3 for average, 2 for below average, and 1 for homely or not good looking. Raters are reminded to use the common people in the Chinese population, not the sample analysts, as the benchmark for rating. Moreover, age should not be considered in rating. That is, the rating score should not depend on how young or old the rated person is. Rather, the rating score should be solely based on the rater's judgment of the person's prettiness or handsomeness.

To diversify the tastes for beauty, we select 30 raters with different backgrounds in social experience, economic income, and academic experience. Specifically, our raters include 4 undergraduate students from the Chinese University of Hong Kong, 19 PhD students from various universities in mainland China, 3 PhD students from the Chinese University of Hong Kong, a Big 4 accountant, an accounting faculty member, a brokerage trader, and a CFO in a large private company from mainland China. In total, 14 of the raters are male and 16 female.

We use the following formula to obtain a summary beauty rating S for analyst i:

$$S_i = \frac{1}{K}\sum_{k=1}^{K}(s_{ki} - \overline{s_k}), \tag{1}$$

in which, s_{ki} denotes the beauty rating by rater k for analyst i and $\overline{s_k}$ is the average rating score of rater k across all analysts. By this measure we essentially control for each rater's fixed effect in the analysis.

IV. Empirical results

Regression model

To test whether analysts' forecast performance is related to their beauty levels, we estimate the following linear regression model:

$$\textit{Forecast error}_{ijt} = f(\textit{beauty}_i, \textit{controls}) + \varepsilon_{ijt}, \tag{2}$$

in which the subscripts *i*, *j*, and *t* denote analyst *i*, firm *j*, and year *t*, respectively. In our main analysis each analyst contributes only one forecast for each firm year. We calculate the dependent variable, *Forecast error*, following Clement (1999). First, for the earnings forecast by analyst *i* for firm *j* in year *t* we calculate its absolute forecast error ($absFE_{ijt}$) as $|forecast_{ijt} - actual\ earning_{jt}|$. Then we calculate the average of the absolute forecast error ($averageFE_{jt}$) for firm *j* in year *t* across forecasts by all analysts. Forecast error of analyst *i* is measured as $(absFE_{ijt} - averageFE_{jt})/averageFE_{jt}$. The measure controls for firm-year effect and potential heteroscedasticity related to the magnitude of forecast errors. A larger value indicates a larger forecast error. In China, analysts only provide forecasts for annual earnings. If prettier analysts could obtain better information from management, we suspect that the effect would be strongest when management has the greatest informational advantage over outside parties. Such a circumstance should occur toward the end of the fiscal year (but before earnings announcement), when management either already has a copy of the financial statements to be audited or at least has developed a good understanding of the past year's financial performance. Therefore, in our main analysis, we only include in the analysis the last forecast made in the concerned year by each analyst and also require that the forecast be made between December 1st and the earlier of April 30th of the following year or the earnings announcement date of the concerned year.

We follow the literature to control for various potentially confounding factors. A longer time the analyst has been following the firm, the more likely that the analyst would have developed close personal or business relationship with the firm's executives. The analyst could then have privileged access to corporate inside information. We hence include the variable *Experience in firm* measuring the number of days the analyst has been following the firm till issuing the forecast concerned (detailed definitions of all variables are included in the Appendix 1). Analysts' tenure with the profession could also have an effect on their forecast performance. Certain general research skills, regardless of which specific firm is being followed, could be enhanced over years working as a financial analyst. As such, we include a variable *Experience in profession* in the model. Together these two variables controls for the effect analysts' professional skills and capability on their forecast performance.

We include a variable *Star status*, measuring whether the analyst was a star analyst in the previous year, because star analysts typically wield a large influence in the market and firms may grant them special access to inside information as an exchange for preferred coverage. Analysts' intelligence and education, two factors arguably highly correlated, could also have an impact their forecast accuracy. For this effect, we include a variable *PhD degree* to indicate whether the analyst holds a PhD degree and *Top2 school* to denote whether the analyst was a graduate from Peking University or Tsinghua University, commonly deemed the best two universities of China.

Financial analysts working in larger brokerages enjoy more abundant financial resources and larger professional networks and their brokerages are likely to manifest greater importance to their client firms. Each of these factors could affect the analyst's forecast performance. As such, we include the variable *Brokerage size* to gauge the number of analysts employed by the brokerage hiring the concerned analyst. Although we restrict the forecasts to be made toward or after the end of the fiscal year to maximize the potential effect of beauty, forecast horizon may still play a role in affecting analyst forecast accuracy. The later an analyst issues the forecast, the more information she could incorporate. We hence include in the model a variable *Forecast horizon*. It is measured as the number of days between the forecast date and the fiscal year-end date. In addition, when more analysts cover a firm, together they would produce more information about the firm through their research or through their pressuring the firm to disclose more. Each individual analyst's forecasts are likely then be more accurate as a result. To control for this effect we include a variable *Analyst following* measuring the number of analysts who are issuing reports for the firm in the year.

Finally, certain firm characteristics could be related to analyst forecast accuracy. For instance, larger firms in general are believed to have better information environment. Growth firms, on the other hand, are generally deemed to more opaque because the larger uncertainty about their future development and also because of their larger portion intangible assets. Correspondingly, we include *Firm size* and *Book to market* in the model. When firms are followed by more institutional investors, they would face greater pressure, either implicitly through these investors' investment choice or explicitly through their active participation in corporate governance, to be more informationally transparent. We therefore include *Institutional ownership* measured as the average of the firm's institutional ownership in percentage over the prior four quarters up to the analyst forecast's date. The transparency level of a firm's general information environment could also be reflected in its stock trading. More volatile stock prices could signal higher certainty and a larger trading volume would indicate the presence of more information or disclosure. We hence include *Stock return volatility* and *Trading volume* in the model.

Descriptive statistics

Table 2 exhibits descriptive statistics for variables in our main analysis. *Forecast error* has a median of 0.833 and a much larger mean of 5.618 with a standard deviation 15.894, suggesting the variable is right-skewed in our sample. In alternative specifications, we further use the natural logarithm of original variable and find our conclusions unaffected. Consistent with our earlier notion that the analysts in our sample derived from CSMAR are generally from larger brokerages with more work experience, *Experience in firm* and *Experience in profession* take on relatively large values, mean 4.770 and median 5.869 for the former and mean 7.035 and median 7.254 for the latter. Further supporting this notion, 19.9% of our sample analysts appear were nominated into the star-analysts lists. On average, our sample analysts possess a high level of education. About 14% of them hold a PhD degree and 33.2% of them are from the top2 universities in mainland China. Another observation worth noting is that, on average, the fraction of institutional ownership for our sample firms, which are typically larger than those not in our sample, is relatively low. The mean is 10.145% and median even lower 7.285. These statistics suggest that the common impression that the Chinese stock market is dominated by retail investors and institutional investors in general play a very limited role in leading the market (Gu, Li, and Yang, 2013). This feature of the setting also implies that Chinese financial analysts are likely to have a greater influence in the market than their US counterpart to the extent that retail investors are more easily swayed by “expert opinions” or media.

Table 2 Panel B reports the distribution of the beauty ratings. Our rating results are in general consistent with and comparable to prior research using a similar rating design. For example, the two extreme beauty levels “strikingly beautiful” and “homely” both receive fairly low proportions of ratings (1.52% and 2.62%, respectively). Similarly, about 60% of the analysts are rated to have an average looking. Among all sample analysts, 12.22% of them are rated as above average in looking and 23.52% below average. Although in our main analysis, we use the original scores (after the mean adjustment). In robustness checks, we combine the bottom two and the upper two, respectively, levels of beauty ratings and find that our conclusions remain similar.

To illustrate that our beauty ratings have meaningful variation, we cross-check the rating scores with the anecdotes that large brokerages incline to hire more beautiful analysts as compared to smaller ones. Table 2 Panel C and Figure 1 presents the beauty ratings of analysts from large brokerages as compared to those from small ones. The results support the anecdotes: While small brokerages’ analysts have an average beauty rating of -0.018, those in larger brokerages have an average score of 0.101. This difference is strikingly large considering that it constitutes about a quarter of a standard deviation of the beauty rating (0.467 as in Table 2 Panel A).

Regression results

Table 3 reports the regression results for model (2). Supporting with our prediction, *Beauty* is significantly negative (coeff. = -0.341, $p<0.01$), suggesting that more beautiful or handsome analysts produce forecasts with smaller deviation from the actual earnings.

For control variables, it is worth noting that higher analyst following and greater institutional ownership are both negatively associated with individual analysts' forecast errors, while stock return volatility is positively correlated with forecast errors. These results are consistent with the notion in the literature that they are measures of firms' information environment, but in opposite directions.

V. Market reaction analysis

If beautiful analysts produce more accurate forecasts than do less beautiful ones, we should expect that the market realizes this regularity. In particular, a natural deduction would be that investors would react more strongly to the stock recommendations issued by more beautiful analysts. After all, earnings forecasts are one element of input into the stock recommendation process. To formally test this prediction, we estimate the following linear regression model:

$$CAR(-1, +1)_{ijk} = f(Rate1_{ijk}, Rate2_{ijk}, Rate3_{ijk}, Rate1_{ijk} *Beauty_i, Rate2_{ijk} *Beauty_i, Rate3_{ijk} *Beauty_i)+\varepsilon_{ijk}, \quad (3)$$

in which $CAR(-1, +1)_{ijk}$ is the three day (-1, +1) abnormal market reaction to the stock recommendation by analyst i for firm j in year k; *Rate1* is an indicator equal to 1 if the recommendation is a downward revision or a first-ever sell, strong sell, or hold recommendation through the analyst's following history with the firm and 0 otherwise; *Rate2* is an indicator equal to 1 if the recommendation is maintaining the previous recommendation opinion and 0 otherwise; and *Rate3* is an indicator equal to 1 if the recommendation is an upward revision or a first-ever strong buy recommendation through the analyst's following history with the firm and 0 otherwise.

The regression results are shown in Table 4. Column I shows that analysts' stock recommendations are indeed informative in the Chinese stock market. Positive opinions are associated with significantly positive market reaction while negative opinions are associated with significantly negative market reaction. It is worth noting that even relatively neutral opinions, such as those reflected by *Rate2* = 1, are also viewed positively by investors. A potential reason is that few stock recommendations are in the categories of "strong sell" or "sell". As a result, in most cases, the worst opinions corresponding to *Rate2* = 1 is a maintained Hold.

Our main interest lies in the interaction terms. Column II shows that the interaction of *Beauty* with the relatively positive opinions, *Rate2* and *Rate3*, are both significantly positive. The results support our conjecture that investors rationally perceive recommendations by more beautiful analysts to contain more information in the recommended direction than less beautiful analysts. In column III, the results remain similar when we code the beauty rating into a dummy variable, *Dbeauty*, that equals 1 if beauty is greater than the mean and 0 otherwise.

VI. Privileged information access?

The analysis above shows that beautiful or handsome analysts perform better in forecasting earnings and producing informative stock recommendations. It is, however, not clear whether such superior performance originates from analysts' superior research ability or their privileged access to information because of their better looking. To shed some light on this issue, we explore whether beautiful analysts have privileged information access with management or other parties possessing inside information. For this purpose we test whether more beautiful analysts are more likely to issue research reports conveying inside information right before significant corporate news than less beautiful analysts. We consider three types of corporate events: restructuring, significant business contracts, and earnings warning. To ensure that the analyst has been active such that she has the potential to issue any reports, we require that the analyst have issued at least one report in the calendar-day window (-360, -90) relative to the event date to enter the analysis.

Table 6 Panel A reports results on restricting news. Column I shows that more beautiful analysts are significantly (*Beauty*: coeff. = 0.100, p=0.019) more likely than are less beautiful analysts to issue a stock recommendation in the period (-90, 0) relative to the public announcement of restructuring news. The evidence hence supports beautiful analysts' privileged information access. Further considering that in China, investors typically consider restructuring as positive news and in most cases the market reacts positively to its revelation, beautiful analysts, if they could gain access to inside information, are likely to issue positive opinions in the short period prior to the public announcement of restructuring plans. Indeed, column II confirms this prediction. *Beauty* (coeff.=0.127, p=0.029) is significantly positively associated with the likelihood of the issuance of a "strong buy" recommendation in the (-90, 0) window. As a contrast, column III shows that beautiful analysts do not differ from less beautiful ones in issuing negative opinions ("hold," "sell," or "strong sell") in this short pre-event window.

Regression results for the control variables suggest that other factors, such as competition among analysts (*Analyst following*), length of time following a firm (*Experience in firm*), star-analyst status (*Star status*), alma mater (*Top2 school*), and resources of the brokerage (*Brokerage size*) also play important roles in helping analysts gain access to inside information.

Table 6 Panel B reveals a similar relation between analysts' beauty level and their likelihood of issuing a stock recommendation in the short period (-90, 0) prior to the public announcement of important business contracts. Specifically, more beautiful analysts are significantly more likely to update their recommendations right before the public announcement of the contracts

(*Beauty*: coeff. = 0.204, $p < 0.001$). In columns II and III, we do not find any systematic patterns for beautiful analysts to issue positive or negative opinions in advance, potentially because the news contained in these contracts is not universally good or bad.

Table 6 panels C and D examine beautiful analysts' early access to information in the settings of positive and negative earnings warnings by management. CSRC requires publicly traded firms to issue public warnings if the current year's earnings differ from the prior year's by more than 50% or the earning is flipping from a profit in the prior year to a loss in the current year or vice versa. Compared to other corporate events, earnings warnings are much less ambiguous in terms of the positive/negative direction of the news. As a result, the prediction for beautiful analysts, to the extent they have privileged information access, to issue favorable or unfavorable recommendation in advance is more straightforward.

Similar to the results in panels A and B, Table 6 Panel C column I shows that *Beauty* is significantly positively (coeff. = 0.067, p=0.081) correlated with analysts' likelihood of updating their earlier recommendation in the short window (-90, 0) prior to warnings of positive earnings news. Columns II and III further demonstrate that more beautiful analysts are more likely to update with a favorable recommendation, i.e., "strong buy," but not a negative one.

In Table 6 Panel D for management warning about negative earnings news, we do not find in column I that more beautiful analysts are overall more likely to update their stock recommendations. However, in column III we do find that more beautiful analysts are more likely to update their recommendation with a negative opinion (*Beauty* coeff. = -0.308, p=0.004).

Overall, the results in this section suggests that beautiful analysts have early access to information about pending corporate news to be public released.

VII. Information acquisition

The test in the previous section does not directly examine analysts' information acquisition process. The early access to inside information may not be granted by management but rather provided by other parties close to such information. To directly examine the role of management in shaping the relation between analysts' beauty and their job performance, we conduct analysis in the setting of site visits by analysts. Here, analysts need to directly interact with management to obtain information.

Since 2007, firms publicly listed at the Shenzhen Stock Exchange have been required to formally disclose site visits by financial analysts and institutional investors. Table 5 Panel A shows that the number of firms disclosing at least one site visit has been increasing, with a particular large jump in 2012. On average, each firm receives 5 to 9 site visits. A typical site visit is conducted by analysts alone or analysts together with their client institutional investors. Actually liaising with public firms to arrange these meetings constitutes an important type of service of analysts for their client investors. When not accompanied by clients, analysts would call their clients, presumably on a timely basis to convey any valuable information they garnered in the site visit. Therefore, it is reasonable to believe that the market reaction surrounding the site visits fairly measure the information acquired through the analysts in these visits. To allow some time for analysts and their clients to process the information before making their investment decisions, we use a relatively wide, 5-day window (-2, +2) to measure the market reaction. Because the news coming out of the site visit could be either good or bad, we use the absolute value of the cumulative abnormal returns.

Table 5 Panel B shows that indeed, analysts' beauty level is significantly positively associated with the absolute market reaction around the site visit (ceoff. = 0.095, p=0.018), supporting our conjecture that more beautiful analysts gain advantage when prying for information from management. Results for several control variables are consistent with expectations. For instance, larger brokerages (*Brokerage size*) and the presence of more institutional investors (*Institutional ownership*) are correlated with more information conveyed in the site visits. In addition, site visits are more informative when the firm is surrounded by great uncertainty (*Stock return volatility*).

VIII. Management discrimination in information disclosure?

To follow our logic of inquiry, our final set of tests is to investigate whether the privileged information access enjoyed by more beautiful analysts, which leads to their better job performance, is granted by managers intentionally, perhaps because they enjoy spending time with these analysts. If managers depend on analysts for communicating information, attracting investors, especially the institutional type, and tilting the market in their preferred direction, they should care more about analysts' skills while not indulge their tastes of beauty to the extent that the two types of characteristics are not perfectly correlated. As such, we would expect that, when managers are more concerned with their stock's performance, they would be less affected by beauty in disclosing information. Correspondingly, beauty would play a smaller role in improving analysts' forecast performance. The opposite line of reasoning would also true.

For empirical tests, we exploit two settings with opposite effects on managers' interest in their own firm's stock. One is the unlocking of the non-tradable shares, a reform started in 2005 and primarily among SOEs, and the other is the closure of the share pledging borrowing by controlling shareholders.

Prior to the enforcement of the non-tradable share reform in 2005, shares of Chinese listed companies were classified into non-tradable shares (held by founders, affiliated firms, managers, etc.) and tradable shares. The non-tradable shares accounted for 60% of total shares on average (Xiao 2015). The dual structure of ownership created significant conflicts of interests between holders of non-tradable shares and investors of tradable shares. In 2005 the China Security Regulatory Committee required all listed firms to convert their non-tradable shares to tradable shares in batches in subsequent years. Starting from 2005, a large amount of non-tradable shares were sold by large shareholders and managers every year, reaching to 10 billion RMB in 2009 (Xiao 2015). Because managers, or the controlling shareholder they represent, have a large equity holding to sell they are motivated to increase stock liquidity and enhance the market's valuation of their firms' stocks. Sell-side financial analysts play important roles in both aspects. Therefore, managers are likely to value the abilities and skills of financial analysts more after the non-tradeable shares reform, and, as a result, we expect their beauty taste-based discrimination among financial analysts to decline significantly after the stock reform. However, if the more favorable treatment that managers offer to attractive analysts is due to managers' unintentional bias or due to superior communication and social skills of attractive analysts then we should not expect to see changes in managers' behavior, because these latter causes are unlikely to be affected by the stock reform. To summarize, we expect that the reduction effect of analysts' beauty on their forecast error is more salient before the unlocking reform than after. Because the unlocking could be conducted in multiple batches, we focus our analysis on the first batch.

For the latter, to ease financial constraint, it is a relatively common practice for controlling shareholders to pledge a portion of their equity ownership with the bank for loans. Hao and Liang (2009) show that about 50% (20%) private owned (state owned) firms used stock pledge over the period from 2004 to 2007. While in a pledge contract, the controlling shareholder could be asked to supply additional collateral or fund if the stock price declines to some critical level. The controlling shareholder and her manager would then pay special attention to ensure that the stock price is kept at a desired high level. During this period, the manager is less likely to allow beauty to sway her decision about which analysts to rely on for influencing the market. Hence, we expect that the effect of beauty on analysts' forecast error is more significant after the end of the stock rights pledge contract than before.

Table 7 presents the empirical results. Panel A column I shows that in the two years prior to the unlocking of the first batch of non-tradable shares, analysts' beauty levels are significantly negatively associated with their forecast errors (coeff. = -0.868, p= 0.018). However, as shown in column II, in the two years after the first batch of unlocking, *Beauty* is no long significantly correlated with forecast error. The Chi-square test suggests that the difference of the coefficients of *Beauty* between the models are statistically significant (p=0.06). The results are hence consistent with our prediction above.

Similarly, Table 7 Panel B indicates that while analysts' beauty is not significantly associated with their forecast error before the closure of the stock rights pledge contract, the relation turns significantly negative after the expiration of the contract. The Chi-square test suggests that the difference of the beauty effect is statistically significant between the two periods (p=0.05).

Overall, the results in this section suggests that at least a portion of the information access privilege enjoyed by beautiful analysts derives from managers' tastes for beauty that is rooted in skills or abilities.

IX Career consequences

Up to this point we have shown that beautiful analysts deliver better job performance in forecasting and recommending stocks than less beautiful analysts, at least partially because of their more attractive physical appearance. A natural follow-up question is how far does this beauty effect carry in an analyst's career? Especially, does beauty further have an impact on analysts' career opportunities? To shed some light on this issue, we investigate whether analysts with a higher level of beauty are more likely to be voted into the star-analysts lists and be hired by a large brokerage from a smaller one, after controlling for various potentially confounding factors such as diligence, intelligence, experience, skills, resources, and even job performance.

For the star analyst nomination test, we define a dependent variable *Star rank* that equals 5 if the analyst is ranked at the 1st place in the New Fortune Star-analyst list, 4 the 2nd place, and so on, and 0 if the analyst is not selected into the list. The test uses ordered logit regression. We control for analysts' professional experience (*Experience*) by measuring the number of years she has been publishing research reports according to the record in CSMAR. We measure an analyst's diligence level using two variables, the *number of recommendations issued* and the *number of stocks followed* by the analyst. Consistent with our analysis in the previous sections, an analyst's job performance is gauged by the average informativeness level of her stock recommendations (*Recommendation informativeness*) and her relative ranking if earnings forecast accuracy (*Accuracy ranking*) measured following Hong and Kubik (2003). The *Brokerage size* measures the resources available to the analyst. Finally, we control for an analyst's intelligence and skills by considering whether she has a PhD degree and whether she graduated from the two top schools of China.

Empirical results are tabulated in Table 8 column I. *Beauty* is significantly positively correlated with analysts' ranking in the star competition, suggesting that physical appearance does grant the endowed analyst with greater career advantage. Notably, professional experience (*Experience*), diligence as measured by the recommendation frequency (*number of recommendations issued*), but not the coverage breadth (*number of stocks followed*) perhaps because of lack of focus and hence lack of depth and insights, job performance as measured by stock recommendation informativeness, brokerage size, and the school attended also all matter for the chance of being ranked at a higher place in the star analyst list.

To study whether a more beautiful analyst is more likely to be hired from a smaller brokerage and a large one, we construct an indicator as the dependent variable *Switch to a top10 brokerage* that equals 1 if the analyst is hired by a top 10 brokerage from a non-top 10 one in the year and 0 otherwise. The size of the brokerage is measured by both the number of analysts employed (*size*, as in column II) and amount of trading commission procured (*commission*, as in column III). Besides all the control variables included in column I, we additionally include the indicator *Star status* to control for the career impact of being nominated into the star analyst list.

Table 8 column II shows that *Beauty* is significantly positive (coeff. = 0.610, p=0.008). The evidence suggests that in any given year, a more beautiful analyst is more likely to switch from a small brokerage to a top 10 brokerage even after controlling for various other factors that are directly or indirectly related to job performance. In column III, when we measure brokerage size using trading commission instead of size of the analyst group, we find similar results. Overall, it appears that beauty not only just has an effect on analysts' job performance, but also on their career opportunities.

X. Conclusion

We study the effect of an ascriptive attribute of analysts', namely, beauty as assessed based on head-to-shoulder ID-type of photos, on their job performance and investigate whether beauty taste-based selective disclosure by management is an underlying reason of this effect. Our results show that more beautiful analysts make more accurate forecasts and produce more informative stock recommendations. More beautiful analysts seem to be able to gain advance access to information about pending significant corporate events. Their corporate site visits observe greater price reaction in the market. When managers are concerned about their firms' stock performance, as when their firms' controlling shareholders are bound by stock rights pledge contracts or after the controlling shareholders procure the flexibility to sell their equity holdings after the non-tradable shares' unlocking, beauty has little effect in gaining the analyst informational advantage. Finally, beauty reaches beyond affecting analysts' performance and has a direct impact on their career opportunities such as the chance of being nominated into a top spot in the star-analyst list and finding a job in a large brokerage over time.

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Appendix 1 Variable definition

Forecast error	Calculated following Clement (1999). First, for earnings forecast by analyst *i* (in our main analysis, each analyst contributes only one forecast each firm year) of firm *j* in year *t* we calculate its absolute forecast error ($absFE_{ijt}$) as $\|forecast_{ijt} - actual\ earning_{jt}\|$. Then we calculate the average absolute forecast error ($averageFE_{jt}$) for firm j in year t across forecasts by all analysts. Error of forecast by analyst *i* is measured as $(absFE_{ijt} - averageFE_{jt})/averageFE_{jt}$. The measure controls for firm-year effect and potential heteroscedasticity. A larger value indicates a larger error.
Beauty	Rating of each analyst's beauty level, calculated as ($rating_{ki} - average\ rating_k$) averaged across the 30 raters, in which, $rating_{ki}$ is rater *k*'s beauty score for analyst *i* and $average\ rating_k$ is rater *k*'s average rating across all analysts.
Firm experience	Length of time that the analyst has been following the concerned firm, measured as the logarithm of the number of days from the date on the analyst's first report covering the firm in CSMAR and the date of the concerned forecast.
Experience in profession	Length of time that the analyst has been in the profession, measured as the logarithm of the number of days from the date of the analyst's first report in CSMAR and the date of the concerned forecast.
Star status	An indicator equal to 1 if the analyst was a star analyst in the previous year and 0 otherwise.
PhD degree	An indicator equal to 1 if the analyst has a PhD degree and 0 otherwise.
Top2 school	An indicator equal to 1 if the analyst graduated from Peking University or Tsinghua University and 0 otherwise.
Brokerage size	Natural logarithm of the number of analysts employed by the brokerage.
Forecast horizon	The number of days from the forecast date to the end of the fiscal year (i.e., Dec 31).
Analyst following	Natural logarithm of the number of analysts following the firm.
Firm size	Natural logarithm of the firm's market capitalization at the beginning of the year.
Book to market	The ratio of book value of equity to market capitalization measured at

	the beginning of the year.
Institutional ownership	Average of the firm's institutional ownership over the prior four quarters.
Stock return volatility	Standard deviation of daily stock returns calculated through the year.
Trading volume	Natural logarithm of the firm's total trading volume in RMB through the year.

Figure 1 Analysts' beauty level and brokerage size

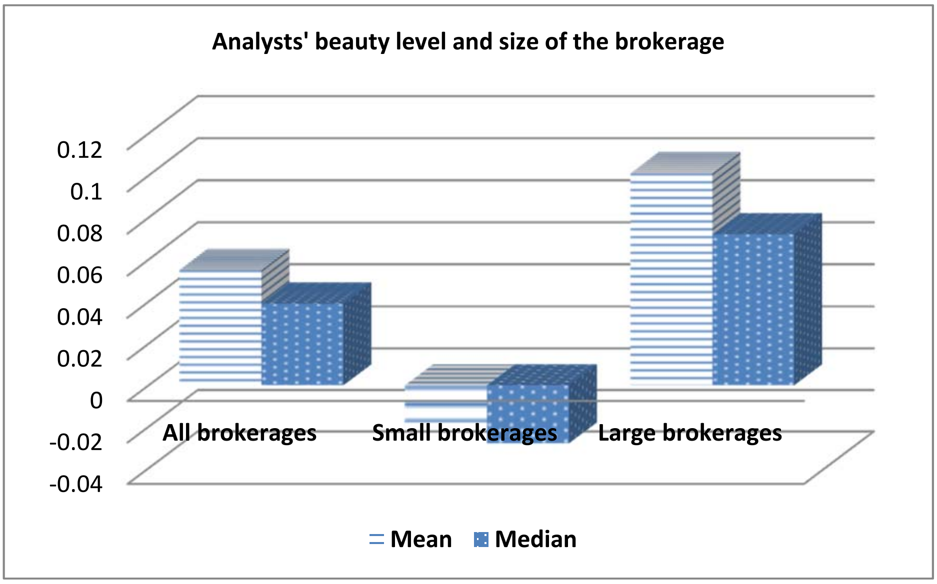

Table 1 Sample

Analysts in our sample are the intersection of those who had registered with the Securities Association of China (SAC) by the end of Dec 31, 2011 and those covered by the CSMAR database. Sample period is from 2005 to 2014.

Year	No. of analysts	No. of brokerages	No. of stocks	No. of forecasts	No. of stock recommendations
2005	408	50	717	7,912	9,636
2006	461	47	920	19,362	23,305
2007	740	54	1,050	11,921	15,252
2008	1,073	68	1,103	16,584	22,004
2009	1,345	72	1,471	25,669	30,571
2010	1,571	82	1,782	25,783	38,264
2011	1,457	78	1,998	32,007	43,427
2012	1,266	82	2,042	35,750	46,554
2013	1,009	66	1,873	30,475	36,320
2014	782	63	1,925	24,779	28,323
total	2,183	106	2,648	230,242	293,656

Table 2 Descriptive statistics

The statistics are calculated based on the sample of last-of-the-year earnings forecasts by each analyst.

Panel A Variables in the main analysis

Variable	Mean	Std	P25	P50	P75	N
Forecast error	5.618	15.894	-0.125	0.833	4.000	72,210
Beauty	0.055	0.467	-0.228	0.039	0.305	72,210
Experience in firm	4.770	2.706	3.664	5.869	6.783	72,210
Experience in profession	7.035	0.926	6.688	7.254	7.653	72,210
Star status	0.199	0.399	0.000	0.000	0.000	72,210
PhD degree	0.140	0.347	0.000	0.000	0.000	72,210
Top2 school	0.332	0.471	0.000	0.000	1.000	72,210
Brokerage size	3.829	0.611	3.466	3.932	4.277	72,210
Forecast horizon	68.785	98.147	-11.000	64.000	134.000	72,210
Analyst following	3.359	0.696	2.944	3.466	3.871	72,210
Firm size	16.050	1.301	15.108	15.809	16.807	72,210
Book to market	0.388	0.264	0.194	0.319	0.512	72,210
Institutional ownership	10.145	11.192	3.834	7.285	12.301	72,210
Stock return volatility	2.810	0.782	2.249	2.696	3.260	72,210
Trading volume	23.817	1.105	23.029	23.755	24.552	72,210

Panel B Distribution of the beauty ratings

Beauty rating		All analysts	Male analysts	Female analysts
Homely	1	2.62	2.83	2.09
Below average	2	23.52	25.44	18.74
Average	3	60.12	60.55	59.06
Above average	4	12.22	10.15	17.38
Strikingly beautiful/handsome	5	1.52	1.03	2.74
Number of analysts		2,306	1,645	611

Table 2 (cont'd)
Panel C Analysts' beauty level and brokerage size

	Brokerage size based on number of analysts employed			Brokerage size based on trading commissions received		
	No. of analysts	Beauty		No. of analysts	Beauty	
		Mean	Median		Mean	Median
All brokerages	10,112	0.055	0.039	10,112	0.055	0.039
Small brokerages	7,018	-0.018	-0.028	7,115	-0.016	-0.028
Large brokerages	3,094	0.101	0.072	2,997	0.099	0.072
	Diff.	-0.120	-0.100		-0.115	-0.100
	t/z	12.570***	12.270***		11.900***	11.660***

Table 3 Analysts' beauty level and forecast accuracy

The unit of analysis is firm-year-forecast. For this table, we include the last-of-the-year forecast issued before the annual earnings announcement by each analyst for each firm-year. The standard errors are clustered by firm and analyst. P-values are in the parentheses. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 level, respectively.

	Dependent variable = *Forecast error*
Variables	Coefficient (p-value)
Beauty	-0.341***
	(0.008)
Experience in firm	0.056*
	(0.074)
Experience in profession	-0.136
	(0.124)
Star status	0.159
	(0.430)
PhD degree	-0.138
	(0.343)
Top2 school	0.222
	(0.194)
Brokerage size	-0.043
	(0.772)
Forecast horizon	0.038***
	(0.000)
Analyst following	-1.072***
	(0.000)
Firm size	0.567*
	(0.076)
Book to market	1.521*
	(0.082)
Institutional ownership	-0.036***
	(0.004)
Stock return volatility	2.219***
	(0.000)
Trading volume	-0.277
	(0.380)
Constant	5.552
	(0.310)
N	72,210
Adjusted R-squared	0.083

Table 4 Analysts' beauty and informativeness of their stock recommendations

This table examines whether analysts' beauty levels are associated with the market reaction to their stock recommendations. *Rate1* is an indicator equal to 1 if the recommendation is a downward revision or a first-ever sell, strong sell, or hold recommendation through the analyst's following history with the firm and 0 otherwise. *Rate2* is an indicator equal to 1 if the recommendation is maintaining the previous recommendation opinion and 0 otherwise. *Rate3* is an indicator equal to 1 if the recommendation is an upward revision or a first-ever strong buy recommendation through the analyst's following history with the firm and 0 otherwise. *Dbeauty* is an indicator equal to 1 if beauty is greater than the mean and 0 otherwise. The regressions have no intercepts. In all regressions, the dependent variable *CAR(-1, +1)* is the three day (-1, +1) abnormal market reaction to the stock recommendation. Standard errors are clustered by firm. P-values are in the parentheses. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 level, respectively.

	Dependent variable = *CAR(-1, +1)*		
Variables	I	II	III
Rate3	0.015***	0.015***	0.015***
	(0.000)	(0.000)	(0.000)
Rate2	0.006***	0.006***	0.006***
	(0.000)	(0.000)	(0.000)
Rate1	-0.003***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)
*Beauty*Rate3*		0.002**	
		(0.037)	
*Beauty*Rate2*		0.001***	
		(0.000)	
*Beauty*Rate1*		0.000	
		(0.644)	
*Dbeauty*Rate3*			0.002**
			(0.018)
*Dbeauty*Rate2*			0.001***
			(0.000)
*Dbeauty*Rate1*			-0.000
			(0.708)
N	267,716	267,716	267,716
Adjusted R-squared	0.027	0.027	0.027

Table 5 Analysts' beauty and informativeness of their site visits

This table exhibits the market reaction surrounding analysts' site visits. Sample period is from 2007 to 2014. The unit of analysis is analyst-firm-site visit. Market reaction is measured as the cumulative market-adjusted abnormal return over the trading-day window (-2, +2) with 0 being the site visit date. Standard errors are clustered by firm and analyst. P-values are in the parentheses. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 level, respectively.

Panel A Site visits statistics

Year	Number of firms in SZEX	Number of firms disclosing any site visits	Average number of site visits per firm
2007	580	219	5.17
2008	674	215	5.57
2009	739	315	7.69
2010	876	453	8.91
2011	1,023	394	7.29
2012	1,148	880	7.16
2013	1,170	811	5.79
2014	1,188	803	5.51

Panel B Informativeness of site visits

Variables	Dependent variable = |*CAR(-2, +2)*|
Beauty	0.095**
	(0.018)
Experience in firm	0.007
	(0.611)
Experience in profession	0.008
	(0.498)
PhD degree	-0.045
	(0.436)
Top2 school	0.069
	(0.132)
Brokerage size	0.105*
	(0.053)
Analyst following	0.012
	(0.811)
Firm size	0.029
	(0.627)
Book to market	0.038
	(0.801)
Institutional ownership	0.009*
	(0.073)
Stock return volatility	1.327***
	(0.000)
Trading volume	-0.054
	(0.322)
Constant	0.483
	(0.618)
N	27,926
Adjusted R-squared	0.066

Table 6 Analysts' beauty and their likelihood of issuing recommendations before significant corporate events

For panels C and D, CSRC requires firms to issue public warnings if the current year's earning differs from the prior year's by more than 50% or the earning is flipping from a profit in the prior year to a loss in the current year or vice versa. To enter the analyses here, analysts are required to have issued at least one report in the calendar day window (-360, -90) relative to the event date. CAR7 is the market-adjusted cumulative return over the window (-3, +3) surrounding the event date. Other variables are defined in the Appendix. All panels use Poisson regressions. Standard errors are clustered by firm. P-values are in the parentheses. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 level, respectively.

Panel A Stock recommendations before the public announcement of restructuring news

Variables	I Issuance of any recommendation opinions in the (-90, 0) window	II Revise upward or issue a "strong buy" opinion in the (-90, 0) window	III Revise downward or issue a "strong sell", "sell" or "hold" opinion in the (-90, 0) window
Beauty	0.100**	0.127**	-0.014
	(0.019)	(0.029)	(0.852)
CAR7	-0.029	0.104	-0.725***
	(0.834)	(0.460)	(0.002)
Analyst following	0.615***	0.692***	-0.004
	(0.000)	(0.000)	(0.954)
Firm size	0.025	-0.010	0.100**
	(0.303)	(0.776)	(0.024)
Book to market	0.067	-0.217**	0.544***
	(0.314)	(0.045)	(0.001)
Institutional ownership	-0.000	0.005***	-0.004
	(0.753)	(0.003)	(0.189)
Stock return volatility	0.011	-0.002	0.155***
	(0.678)	(0.951)	(0.006)
Trading volume	-0.030	0.099***	-0.120**
	(0.203)	(0.001)	(0.015)
Experience in firm	0.064***	0.035	0.125***
	(0.000)	(0.229)	(0.000)
Experience in profession	-0.013	0.024	-0.086
	(0.717)	(0.700)	(0.202)
Star status	0.233***	0.386***	0.067
	(0.000)	(0.002)	(0.363)
PhD degree	0.015	0.081	-0.181**
	(0.751)	(0.358)	(0.017)
Top2 school	0.146***	0.104*	0.072
	(0.006)	(0.098)	(0.377)
Brokerage size	0.613***	0.532***	0.399***
	(0.000)	(0.006)	(0.000)
Constant	-4.656***	-8.493***	-2.423***
	(0.000)	(0.000)	(0.008)
N	131,859	131,859	131,859

Table 6 (cont'd)
Panel B Stock recommendations before the public announcement of important business contracts

Variables	I Issuance of any recommendation opinions in the (-90, 0) window	II Revise upward or issue a "strong buy" opinion in the (-90, 0) window	III Revise downward or issue a "strong sell", "sell" or "hold" opinion in the (-90, 0) window
Beauty	0.204***	0.089	0.140
	(0.000)	(0.275)	(0.359)
CAR7	0.173	0.436*	-1.011*
	(0.410)	(0.098)	(0.050)
Analyst following	0.602***	0.622***	-0.040
	(0.000)	(0.000)	(0.616)
Firm size	0.081*	0.152***	0.259***
	(0.061)	(0.002)	(0.000)
Book to market	0.045	-0.218	0.628***
	(0.691)	(0.149)	(0.001)
Institutional ownership	0.002	0.006***	-0.005
	(0.121)	(0.004)	(0.344)
Stock return volatility	0.087*	0.097	0.215***
	(0.079)	(0.109)	(0.002)
Trading volume	-0.078*	-0.061	-0.223***
	(0.052)	(0.292)	(0.002)
Experience in firm	0.034	0.073	0.072
	(0.238)	(0.112)	(0.179)
Experience in profession	-0.115*	-0.116	-0.059
	(0.057)	(0.220)	(0.524)
Star status	0.210**	0.297**	0.084
	(0.013)	(0.016)	(0.598)
PhD degree	-0.025	-0.092	-0.102
	(0.753)	(0.404)	(0.465)
Top2 school	0.015	0.053	0.024
	(0.832)	(0.517)	(0.863)
Brokerage size	0.622***	0.502***	0.349***
	(0.000)	(0.007)	(0.000)
Constant	-4.029***	-6.682***	-2.523**
	(0.000)	(0.000)	(0.043)
N	44,555	44,555	44,555

Table 6 (cont'd)

Panel C Stock recommendations before firms' warning on significant positive earnings news

Variables	I Issuance of any recommendation opinions in the (-90, 0) window	II Revise upward or issue a "strong buy" opinion in the (-90, 0) window	III Revise downward or issue a "strong sell", "sell" or "hold" opinion in the (-90, 0) window
Beauty	0.067*	0.131*	-0.009
	(0.081)	(0.053)	(0.918)
CAR7	-0.006	0.057	0.162
	(0.975)	(0.824)	(0.709)
Analyst following	0.661***	0.667***	-0.085
	(0.000)	(0.000)	(0.338)
Firm size	-0.013	-0.030	0.073
	(0.748)	(0.481)	(0.306)
Book to market	-0.177*	-0.478***	0.530**
	(0.069)	(0.000)	(0.016)
Institutional ownership	0.001	0.002	0.000
	(0.764)	(0.266)	(0.940)
Stock return volatility	0.019	0.041	0.157**
	(0.682)	(0.363)	(0.032)
Trading volume	-0.053	0.042	-0.072
	(0.199)	(0.351)	(0.349)
Experience in firm	0.040*	0.058*	0.128**
	(0.083)	(0.084)	(0.027)
Experience in profession	-0.019	0.058	-0.150**
	(0.670)	(0.477)	(0.025)
Star status	0.295***	0.363***	0.048
	(0.000)	(0.008)	(0.681)
PhD degree	0.031	0.107	-0.182
	(0.634)	(0.285)	(0.116)
Top2 school	0.091*	0.023	0.103
	(0.095)	(0.745)	(0.187)
Brokerage size	0.655***	0.505**	0.388***
	(0.000)	(0.011)	(0.000)
Constant	-3.503***	-6.771***	-2.467**
	(0.000)	(0.000)	(0.032)
N	34,749	34,749	34,729

Table 6 (cont'd)

Panel D Stock recommendations before firms' warning on significant negative earnings news

Variables	I Issuance of any recommendation opinions in the (-90, 0) window	II Revise upward or issue a "strong buy" opinion in the (-90, 0) window	III Revise downward or issue a "strong sell", "sell" or "hold" opinion in the (-90, 0) window
Beauty	-0.079	-0.046	-0.308***
	(0.262)	(0.680)	(0.004)
CAR7	-0.619	-0.515	-0.787
	(0.292)	(0.534)	(0.199)
Analyst following	0.505***	0.631***	0.132*
	(0.000)	(0.000)	(0.065)
Firm size	0.240***	0.215**	0.227***
	(0.001)	(0.039)	(0.002)
Book to market	0.265	0.289	0.164
	(0.124)	(0.247)	(0.457)
Institutional ownership	0.003	0.001	0.007**
	(0.259)	(0.867)	(0.031)
Stock return volatility	0.124	0.321***	0.050
	(0.123)	(0.003)	(0.618)
Trading volume	-0.092	0.005	-0.142*
	(0.223)	(0.961)	(0.096)
Experience in firm	0.075**	0.049	0.127*
	(0.050)	(0.433)	(0.055)
Experience in profession	0.033	0.025	0.013
	(0.649)	(0.780)	(0.882)
Star status	0.134	0.380**	0.073
	(0.178)	(0.030)	(0.449)
PhD degree	-0.021	0.006	-0.244*
	(0.820)	(0.970)	(0.097)
Top2 school	0.305***	0.122	0.308***
	(0.000)	(0.186)	(0.004)
Brokerage size	0.610***	0.474*	0.572***
	(0.000)	(0.060)	(0.000)
Constant	-7.289***	-10.864***	-4.964***
	(0.000)	(0.000)	(0.001)
N	10,479	10,461	10,459

Table 7 Effect of beauty on analysts' forecast accuracy and managers' attention on stock prices

In panels A and B we require the proportion of unlocked or pledged, respectively, ownership to be greater than 10% of the firm's total equity. In panel A, column I (II) includes analyst forecasts made in the two years prior to (after) the unlocking of the non-tradable shares. In Panel B, column I includes forecasts made in the period while the affected ownership is in pledge and column II includes forecasts made in the two years after the conclusion of the pledge. P-values are in the parentheses. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 level, respectively.

Panel A Unlocking of non-tradable shares

	Dependent variable = *Forecast error*	
Variables	I: Pre-unlocking	II: Post-unlocking
Beauty	-0.868**	0.237
	(0.018)	(0.513)
Experience in firm	0.043	0.058
	(0.692)	(0.575)
Experience in profession	0.084	-0.070
	(0.779)	(0.838)
Star status	0.626	-1.146**
	(0.295)	(0.011)
PhD degree	-0.470	0.276
	(0.495)	(0.626)
Top2 school	0.087	0.994**
	(0.878)	(0.037)
Brokerage size	-1.019	-0.308
	(0.160)	(0.340)
Forecast horizon	0.035***	0.037***
	(0.000)	(0.000)
Analyst following	-1.131	-0.947
	(0.470)	(0.235)
Firm size	0.700	0.681
	(0.514)	(0.593)
Book to market	1.033	4.508
	(0.747)	(0.186)
Institutional ownership	-0.060	-0.029
	(0.220)	(0.597)
Stock return volatility	1.945	0.923
	(0.132)	(0.513)
Trading volume	0.918	0.063
	(0.411)	(0.966)
Constant	-25.050	1.793
	(0.271)	(0.934)
N	6,977	9,059
Adjusted R-squared	0.081	0.073

Chi-square for the difference of the coefficients on *Beauty* between columns I and II = 3.44, p=0.06.

Table 7 (cont'd)
Panel B During and post the closure of the stock rights pledging contract

	Dependent variable = *Forecast error*	
Variables	I	II
Beauty	0.491	-0.820**
	(0.348)	(0.013)
Experience in firm	0.253**	0.187**
	(0.013)	(0.044)
Experience in profession	-0.831*	-0.219
	(0.093)	(0.600)
Star status	-0.335	-1.067**
	(0.657)	(0.042)
PhD degree	-0.978**	0.984
	(0.027)	(0.169)
Top2 school	0.705	-0.434
	(0.128)	(0.489)
Brokerage size	0.007	0.042
	(0.986)	(0.905)
Forecast horizon	0.039***	0.036***
	(0.000)	(0.000)
Analyst following	-2.461***	-2.824***
	(0.002)	(0.001)
Firm size	2.779**	1.749
	(0.011)	(0.178)
Book to market	3.429	-0.857
	(0.351)	(0.788)
Institutional ownership	-0.011	-0.085
	(0.857)	(0.184)
Stock return volatility	3.348**	0.286
	(0.021)	(0.835)
Trading volume	-1.583	-1.286
	(0.167)	(0.222)
Constant	14.306	23.738
	(0.434)	(0.146)
N	4,022	3,542
Adjusted R-squared	0.163	0.112

Chi-square for the difference of the coefficients on *Beauty* between columns I and II = 3.76, p=0.05.

Table 8 Analysts' beauty level and their likelihood of being voted into the star-analyst list and of being hired by a top10 brokerage

The unit of analysis is analyst-year. Column I uses order probit regression. *Star rank* equals 5 if the analyst is ranked at the first place in the New Fortune Star-analyst lists, 4 the second, and so on, and 0 if the analyst is not selected into the list. Columns II and III use logistic regressions. The indicator *Switch to a top10 brokerage* equals 1 if the analyst is hired by a top10 brokerage from a non-top10 brokerage in the year and 0 otherwise. Column II classifies top10 vs. non-top10 brokerages based on size, namely, number of analysts employed and column III based on the amount of trading commissions received in the year. In columns II and III, analysts already being employed by a top10 brokerage are excluded. *Experience* is the analyst's professional experience measured as the number of years since the publication of her first report in CSMAR. *Number of recommendations issued* measures the number of recommendations issued by the analyst in the year concerned. *Number of stocks followed* is the number of unique stocks covered by the analyst in the year concerned. *Recommendation informativeness* is measured as the average of the informativeness of all recommendations issued by the analyst; recommendation informativeness is measured as the three-day (-1, +1) cumulative market-adjusted stock returns for "buy" or "strong buy" recommendations and the opposite of it for "hold", "sell", or "strong sell" recommendations. *Accuracy ranking* is calculated following Hong and Kubik (2003): We first rank the analyst on the basis of forecast accuracy among analysts following the same firm and normalize the ranking on a scale from 0 to 100. An analyst's overall *Accuracy ranking* is her average ranking score across all firms she is following in the year. Other variables are defined in the Appendix 1. P-values are in the parentheses. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 level, respectively.

Variables	I Dep var. = *Star rank*	II Dep var. = *Switch to a top10 brokerage (size)*	III Dep var. = *Switch to a top10 brokerage (commission)*
Beauty	0.117*	0.610***	0.416**
	(0.068)	(0.008)	(0.046)
Experience	0.135***	-0.012	0.120**
	(0.000)	(0.849)	(0.032)
Number of recommendations issued	0.009***	-0.007	-0.008**
	(0.000)	(0.113)	(0.013)
Number of stocks followed	-0.016***	0.007	0.003
	(0.000)	(0.492)	(0.737)
Recommendation informativeness	3.583***	3.896	4.936
	(0.000)	(0.328)	(0.178)
Accuracy ranking	-0.081	0.085	-0.381
	(0.589)	(0.886)	(0.509)
Brokerage size	1.053***	0.503**	0.877***
	(0.000)	(0.032)	(0.000)
Star status		1.164***	1.369***
		(0.000)	(0.000)
PhD degree	0.109	-0.291	-0.323
	(0.272)	(0.347)	(0.256)
Top2 school	0.148**	0.553***	0.708***
	(0.019)	(0.002)	(0.000)
Constant		-3.395***	-5.318***
		(0.000)	(0.000)
N	9,178	4,783	5,088