

Deng, Weiguang; Li, Dayang; Zhou, Dong

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Beauty and Job Accessibility: New Evidence from a Field Experiment

By WEIGUANG DENG, DAYANG LI, DONG ZHOU*

Abstract: This study uses a field experiment to resolve the difficulties of quantifying personal appearance and identify a direct causal relationship between appearance and employment in China. The experiment reveals that taste-based pure appearance discrimination exists at the pre-interview stage. There are significant gender-specific heterogeneous effects of education on appearance discrimination: having better educational credentials reduces appearance discrimination among men but not among women. Moreover, attributes of the labor market, companies, and vacancies matter. Beauty premiums are larger in big cities with higher concentrations of women and in male-focused research positions. Similarly, the beauty premium is larger for vacancies with higher remuneration.

Keywords: appearance discrimination, beauty premium, pre-interview stage, field experiment

JEL Classifications C93, I21, J71

* Deng (First Author): School of Economics and Trade, Hunan University, No. 109 Shijiachong Road, Dist. Yuelu, Changsha, Hunan, P.R. China, 410006 (e-mail: dengweiguang@126.com); Li: Department of Economics, University of California, Riverside, 900 University Ave., Riverside, CA 92551 (e-mail: dayang.li@outlook.com); Zhou (**Corresponding Author**): Department of Cultural Industry and Management, Shanghai Jiao Tong University, No.800, Dongchuan Rd., Minhang District, Shanghai, China, 200244 (e-mail: dzhou002@sjtu.edu.cn).

1 Introduction

Dating back to Gary Becker (1957), studies widely document appearance discrimination against homely individuals in the labor market and measure the beauty premium or plainness penalty in terms of recruitment, earnings, and promotion. In a pioneering study, Hamermesh and Biddle (1994) attribute wage differentials related to appearance to taste-based discrimination, productivity differences associated with consumers, and occupational crowding. Later studies present further empirical evidence of the beauty premium (Biddle and Hamermesh, 1998; Hamermesh et al., 2002; Fleener, 2005; Fletcher, 2009; Rooth, 2009; Harper, 2010; Hamermesh, 2011; Hamermesh, 2013; López Bóo et al., 2013; Von Bose, 2013; Doorley and Sierminska, 2015; Patacchini et al., 2015; Bruton, 2016).

However, establishing causality is challenging because unobserved factors related to productivity or omitted variables can invalidate estimates in studies using decomposition regressions and delicately designed experimental approaches (Neumark, 2012). Beauty premiums, in terms of either recruitment decisions or wage differentials, measure discriminatory labor market outcomes that incorporate employers' perceptions of productivity differences. In the case of interviews, employers partially observe applicants' productivity and ability, and it is empirically difficult to fully control for factors that affect applicant performance and interviewer perceptions. Therefore, it is hard to clearly disentangle purely taste-based discrimination from statistical discrimination at the interview stage. In this study, we use an innovative experimental design to test whether there is pure taste-based discrimination against ordinary looks at the pre-interview stage in China.

There are few studies on “lookism” in the process of resume selection for interviews. We believe that appearance discrimination is common in China. Despite anti-discrimination laws, some companies in China still explicitly or implicitly require job candidates to provide personal photos, usually including a head shot, when submitting resumes. The new media era makes head shots extremely important because many work-related communications and transactions are completed via webcam, and these activities are directly related to performance evaluation. Hence, our study offers the first evidence to examine facial discrimination in China using an experimental approach.

We conducted a field experiment in which we sent applications to employers in five cities in China for multiple types of vacancies. We created these applications by randomly extracting

recent graduates' resumes from a nationwide sample pool and generating duplicates of resumes that differed only in the attached photo. We then submitted these applications to real jobs posted online. Utilizing fixed effects (FE) models that compare individuals with the same resume but a different photo, we can separate taste-based discrimination from statistical discrimination and measure the extent of appearance discrimination at the pre-interview stage.

Aside from an innovative field experiment, our study is unique in its focus on facial features discrimination. Existing studies investigate discrimination based on other measures of appearance, such as gender, body height, build, and obesity. Unlike these types of discrimination, pure facial appearance discrimination is subjective and hard to measure precisely. We measure facial differences more accurately using experimental tools. We offer the first investigation of the interaction effects between appearance and education with Chinese data. Furthermore, we explore the heterogeneous beauty premium across gender, education, employers, and vacancy characteristics.

We find that appearance discrimination exists in the labor market in China, regardless of gender, education, employers, and vacancy characteristics. Ordinary-looking applicants receive fewer interview opportunities because of taste-based discrimination in facial features. For men, the observed looks penalty can be mitigated through better educational credentials; however, this strategy is not effective for ordinary-looking women. In general, heterogeneous beauty premiums exist across labor market scales, types of companies, and features of the positions posted.

Section 2 reviews the existing literature on the economics of beauty and recent studies that are based on experimental design. Section 3 lays out our field experimental design, while section 4 presents the results. The final section summarizes the results and draws conclusions.

2 Review of Literature on Appearance Discrimination

Previous studies on appearance discrimination in the labor market mainly investigate the following dimensions: body weight, height, build (e.g., weight relative to height, or Body Mass Index), and physical appearance (e.g., looks). Discriminatory outcomes are evidenced in wage, employment status, and promotion differentials.

First, many studies analyze the relationship between obesity and labor market outcomes in developed nations, such as the United States and European countries (Quintana-Register and Williams, 1990; Rothblum et al., 1990; Averett and Korenman, 1994; Roehling, 1999; Sarlio-Lahteenkorva and Lahelma, 1999; Cawley, 2004; D'Hombres and Brunello, 2005; Domeque,

2006; Garcia, Greve, 2007; Lundborg et al., 2007; Rooth, 2009). These studies reach similar conclusions: heavier women earn less, while the evidence for men is inconclusive. In terms of developing countries such as China, Jiang and Zhang (2013) find that obesity discrimination exists for women but not for men, especially for middle-income female workers. Specifically, they find that obesity discrimination affects both women's labor market access and their wages.

Second, other studies explore the relationship between height and labor market outcomes. Taller individuals have better jobs with higher earnings and are more likely to be promoted, on average (Judge and Cable, 2004; Blaker et al., 2013). One reason is that taller workers are perceived as healthier and smarter than shorter workers (Blaker et al., 2013). Equivalently, being taller signals fewer absences and higher productivity (Farrell and Stamm, 1988; Ford et al., 2011).

However, height and weight do not fully represent individual appearance and, to some extent, they signal productivity differentials. The third branch of studies turns to looks, or facial and outward appearance.¹ Better-looking individuals earn more (Quinn, 1978; Hamermesh and Biddle, 1994; Hamermesh and Biddle, 2011; Von Bose, 2013; Doorley and Sierminska, 2015; Patacchini et al., 2015). Facial appearance also affects leader choices and voting behaviors (Hamermesh, 2006; Little et al., 2007; Berggren et al., 2010; Ahler et al., 2017). Even human capital formation can be positively influenced by appearance (Mocan and Tekin, 2010; Von Bose, 2013). Besides evidence from developed countries, studies also show the existence of outward appearance discrimination in developing countries such as China (Hamermesh, 1999; Hamermesh et al., 2002; Jiang and Zhang, 2013; Guo et al., 2016; Liu et al., 2016). These studies measure individual appearance using subjective judgments from survey interviewers. Better appearance is positively related to income and employment. Guo et al. (2016) find a non-monotonic relationship in which the beauty premium is larger for the second most beautiful than for the most beautiful.

The existing literature further finds that appearance discrimination varies across gender, companies, and occupations. In terms of gender differences, Hamermesh and Biddle (1994) find that men enjoy a slightly larger premium than women. However, Patacchini et al. (2015) find a beauty premium for women only.² For economic reasons, some enterprises tend to hire attractive applicants. For instance, Fleener (2005) and Bruton (2016) find that the popular

¹ Facial appearance refers to how the combination of eyes, nose, mouth, ears, brow, and facial outline looks. Outward appearance refers to the external image of a human being, including height, figure, and the presence of any disability.

² Hamermesh et al. (2002) also find that beauty raises women's earnings, even after including a wide range of controls.

clothing retailer Abercrombie and Fitch (A&F) prefers to hire attractive store sales clerks. Given that appearance could be an important production factor, good-looking individuals usually sort into occupations where beauty is likely to be more productive (Hamermesh and Biddle, 1994). Generally, attractive individuals are favored in occupations such as clothing sales, clerks, attorneys, and various unskilled positions.

There are several issues in the existing literature. First, appearance discrimination at the pre-interview stage has been generally ignored. Studies focus mostly on discrimination at later stages of the labor market, such as employment, wages, and career advancement. However, the resume screening process can display severe discrimination. Second, appearance measures in the previous literature are not ideal, and how to accurately measure differences in looks is a challenging problem.³ Third, because it is difficult to eliminate bias due to omitted variables and unobserved idiosyncrasies, traditional empirical methodologies may not effectively identify appearance discrimination.⁴

Our study complements current studies from these perspectives by conducting a field experiment. Experimental designs can help isolate causal mechanisms. For instance, in a lab experiment, Heilman and Saruwatari (1979) find that attractive men are consistently preferred in the labor market, but attractive women have an advantage only in non-managerial positions.⁵ Although criticized by Heckman and Siegelman (1993), lab and field experiments have been widely used by researchers to identify causality and find consistent evidence of discrimination (Edelman et al., 2017; Neumark, 2018).

Field experiments, specifically for measuring discrimination, typically include audit and correspondence studies (Harrison and List, 2004; Pager, 2007; Guryan and Charles, 2013; Luo et al., 2015; Neumark, 2012, 2016).⁶ Rooth (2009) designs a field experiment by submitting pairs of facial photos that reflect differences in weight and finds that obese individuals are less likely to be called for an interview. López Bóo et al. (2013) conduct a randomized field experiment by sending fictitious resumes for sales, secretaries, receptionists, or general

³ For example, in Guo et al. (2016), the rating of looks is made by the investigator, which may not match public perception. Additionally, their estimations omit some important influencing factors, such as vacancy requirements.

⁴ Two methods are mainly adopted in previous studies: descriptive statistics (Judge and Cable, 2004; D'Hombres and Brunello, 2005; Garcia and Quintana-Domeque, 2006; Lundborg et al., 2006) and the metering method (Blaker et al., 2013; Hamermesh and Biddle, 2011). Descriptive statistics use statistical technology to identify the current situation of appearance discrimination in the labor market through site surveys or questionnaires. The metering method uses linear regression through the Oaxaca–Blinder decomposition method or sets dummy variables to analyze appearance discrimination in the labor market.

⁵ Heilman and Saruwatari (1979) design a lab experiment with 23/22 male/female undergraduates to evaluate applicants for insurance company vacancies.

⁶ An audit study general uses “live” job applicants with identical-quality resumes. A correspondence study usually just submits paper (or web-based) applications with equal qualifications.

unskilled positions. They find that attractive individuals are more likely to be called for an interview than unattractive individuals and the difference in the beauty premium between women and men is insignificant in Argentina. Patacchini et al. (2015) conduct a field experiment by sending “fake” resumes to examine discrimination against homosexuality and physical appearance in Rome and Milan. They find a beauty premium for women only, and this premium is seemingly much lower when the “pretty” woman is skilled; however, the occupations studied are limited to administrative clerks, bookkeepers, call center operators, receptionists, sales clerks, secretaries, and shop assistants. Additionally, in Ruffle and Shtudiner’s (2015) experiment, they used “almost same” CVs in pairs (one with an attractive or plain picture, the other without a picture) as tools to study the beauty premium in receiving interview in Israel.⁷ They find beauty premiums for attractive men but not for women.

Our study utilizes realistic graduate resumes of pairs of applicants with the same quality but differentiated by photos (“identical twin CVs”). These resumes are randomly distributed to enterprises in different cities through recruiting websites. For accurate measures of facial differences, face blender software is used to mix identification photos of specific individuals with photos of entertainment stars. To alleviate concerns about unobservable productivity differences, we implement a FE analysis that compares interview callback rates for identical twin CVs with different photos. Our contribution to the literature (e.g., Patacchini et al., 2015) is twofold: we provide causal evidence for taste-based appearance discrimination at the pre-interview stage, and we conduct a larger scale field experiment to explore gender differences and heterogeneous effects across different levels of education, diverse labor markets, types of employers, and vacancy features.

3 Experimental Design

3.1 Differentiated Approach

Our experimental design distinguishes itself from previous studies in the following aspects. First, we selected resumes of fresh graduates to avoid potential contamination created by diverse working experience. With resumes drawn from the real job market, we designed identical twin CVs to apply for real vacancies. We are able to estimate the beauty premium by controlling for individual, city, company, and vacancy FE. This allows us to identify the causal

⁷ Except for the picture, the two CVs are different only in some “necessary and negligible” features such as fonts, content order, and names of the large companies in which the candidates acquired working experience.

effect of looks on interview opportunities. Previous studies, in contrast, present ordinary least squares estimates that could be contaminated by omitted variables and unobserved factors. Second, we focused on relatively high-skill occupations (e.g., securities analyst, industry analyst, fund manager, and investment adviser) that require at least a bachelor's degree, compared with the relatively low skill occupations examined by previous studies.⁸ Third, our sample was relatively large, with 658 pairs of identical resumes that differed only in ID photo. The stratified randomized experiment provided sufficient variation since a total of 4,946 pairs of applications were sent for fifteen types of vacancies posted by 818 employers in five large Chinese cities.

3.2 Experimental Instruments: Identical Resumes with Different Looks

Our experiment was implemented between March and November 2016, with assistance from a well-known recruitment platform in Lujiazui, Shanghai.⁹ In the first stage, we randomly selected a total of 673 resumes from the sample pool of the nationwide financial sector, which included seven company types: banks (including credit cooperatives), securities companies (including futures companies), insurance companies, investment companies (including trust companies and investment management companies), Internet-based financial companies, financial consultancy companies, and other financial companies. We eliminated resumes that did not provide critical information, such as gender, college/university, and major. In total, 658 resumes remained.¹⁰ They included 337 women and 321 men.

We then restructured the real resumes into a standardized template (see Appendix 1 for the basic layout). A standardized resume consists of 8 basic attributes: education, international exchange experience, scholarship, research experience, internship, language skills, computer skills, and professional certificates. The detailed contents are shown in Appendix 2. In general,

⁸ López Bóo et al. (2013) investigate these occupations: sales-commercial; administrative-accountancy; marketing-advertisement; secretaries-receptionists-customer service; gastronomy; or general unskilled positions. Patacchini et al. (2015) explore seven occupations: administrative clerk, bookkeeper, call center operator, receptionist, sales clerk, secretary, and shop assistant. Ruffle and Shtudiner (2015) study ten different types of jobs: banking, budgeting, chartered accountancy, finance, accounts management, industrial engineering, computer programming, senior sales, junior sales, and customer service.

⁹ Due to confidentiality agreements, we cannot provide the name of this platform.

¹⁰ The original resume information cannot be released because of personal privacy and confidentiality agreements. We chose the financial industry because the financial sector is a rapidly growing service sector with attractive work opportunities for a wide range of professionals. It has attracted graduates of economics, management, history, social science, science, and engineering. Graduates of economics and management account for approximately 80 percent of applicants, while engineering, science, and law graduates account for 19 percent. Therefore, applications in the financial sector are comprehensive and representative.

our samples comprised fresh graduates with bachelor's or master's degrees, and allowed us to avoid unobserved contamination from working experience.

Our experimental instruments are artificial ID photos on the resumes. In the second stage, we selected four entertainment celebrities commonly considered an attractive woman, an ordinary-looking woman, an attractive man, and an ordinary-looking man, respectively. Based on the appearance of the entertainment star of the same gender, we synthesized the real ID photo on each resume using the portrait synthesizer and Adobe Photoshop software.¹¹ In case of any inappropriateness, further fine adjustments were made to ensure that the original photos had two natural-looking equivalents, one with ordinary looks, and the other with attractive looks.¹² We used different new ordinary names (e.g., Li Li, Qing Luo for women; Ming Chen, Xu Chen for men), phone numbers, and email addresses in each of the twin resumes. To make the twin resumes more realistic, we also made subtle changes in, for example, the birth month, the order of scholarships/certifications, and the name of company for a specific internship (e.g., Bank of China vs. China Construction Bank). In this way, we had a pair of resumes in the sample that differed in facial features but were otherwise basically identical. One group comprised those resumes with attractive appearances, while the other group comprised those with ordinary looks. The two groups have same number of observations.

3.3 Managing Data Limitations

One possible concern relates to the subjectivity of beauty. To check the validity of our designed ID photos, that is, whether they reveal appearance differences, we conducted an online survey in which we asked participants to quickly score the beauty of the two pairs of ID photos shown in Appendix 3. Respondents were asked to score the four different images from 1 to 10 within a half-minute; the larger the score, the more beautiful the appearance. The whole process mimicked the resume selection process. During the survey period, we received 528 valid responses,¹³ comprising 212 men and 316 women with an average age of 28. The gender structure and age distribution of respondents were quite similar to those of realistic enterprise

¹¹ The real and adjusted ID photos cannot be released to protect personal privacy and due to confidentiality agreements.

¹² See Appendix 3: Example of artificially synthesized ID Photos.

¹³ Ruffle and Shtudiner (2015) hired eight judges (four men and four women) to rate the submitted students' pictures; this sample is too small to satisfy the basic requirement for valid estimations.

recruitment departments.¹⁴ The average scores for four ID photos were calculated: Attractive Woman (6.44); Ordinary Woman (4.07); Attractive Man (6.75); Ordinary Man (4.28). The results generally support the validity of our designed ID photos.

Another concern is the potentially limited variation in educational attainment since our sample only included graduates with bachelor's or master's degrees. In China, universities are stratified into groups according to their reputation and quality. High-quality groups enjoy more financial support from the government, as well as better conditions in various aspects. Graduating from a high-quality group signals better human capital and higher ability. On the whole, institutions are grouped as "low-quality universities" (i.e., ordinary universities), "middle-quality universities" (i.e., regular "Project 211" universities), and "high-quality universities" (i.e., "Project 985" universities). All "Project 985" universities are selected from "Project 211" universities.¹⁵ Empirically, we can classify the sample into four types, reflecting the quality of the diploma: Low-Quality Bachelors, Middle-Quality Bachelors, High-Quality Bachelors, and High-Quality Masters. Specifically, Low-Quality/Middle-Quality/High-Quality Bachelors refers to graduates with bachelor's degrees from low-quality/middle-quality/high-quality universities, and High-Quality Masters refers to applicants with master's degrees from high-quality universities.¹⁶ This stratification provides sufficient educational variation and allows us to investigate the relationship between educational credentials and appearance discrimination.

3.4 Experimental Process: Simulating Realistic Applications

We randomly selected vacancies from fifteen types of jobs posted on the platform, such as equity researcher, securities analyst, financial advisor, client manager, and product manager. These vacancies generally require that potential applicants have bachelor's degrees or above. We randomly delivered pairs of resumes with differentiated appearances through an online

¹⁴ We consulted several human resource experts, who provided us with relevant facts and basic statistics of recruitment processes in the labor market.

¹⁵ "Project 985" started on May 4, 1998, and this group includes 38 universities. This project's aim is to establish first-class universities. "Project 211" started in November 1995 and this group contains more schools, including all Project 985 schools. To face the 21st century and meet the challenges of the world's new technological revolution, the Chinese government concentrates resources around construction of 100 world-class universities.

¹⁶ In China, master's degrees from non-high-quality universities are usually no more popular than high-quality bachelor's degrees in the labor market. Thus, we only consider high-quality master's degrees in our study.

recruitment platform to corresponding positions posted by different employers in five cities: Shanghai, Beijing, Shenzhen, Chengdu, and Wuhan.¹⁷

The number of jobs posted differed across cities during the experimental period, and different jobs may require different diplomas, genders, and majors, among other requirements. According to the different requirements of the posted positions (for example, gender, educational attainment, and personality), we sent out corresponding qualified pairs of resumes, delivered within a fixed period after the job was posted. Specifically, only one pair of twin resumes with different looks (i.e., one with ordinary looks and one with attractive looks), in a random order for these two resumes, was delivered for the same position within one-hour intervals for each gender.¹⁸ Additionally, we made sure that enough resumes in each of the four types of diplomas were delivered.

The five selected cities are national or regional financial centers. The first-tier cities, Shanghai, Beijing, and Shenzhen, are national financial centers. The second-tier cities, Chengdu and Wuhan, are the regional financial centers of Western and Central China, respectively. Sufficient recruitment advertisements were posted during the experimental period. Jobs in the financial sector generally are highly remunerated and can attract applications from a wide range of majors, and one vacancy tends to attract a large number of applicants in a short time period. We used stratified randomization processes in our field experiment. Specifically, to truly mimic reality, we considered city-level scales of labor markets and stages of development for each market when we randomly selected the posted vacancies and delivered the resumes. We therefore are not concerned that employers noticed the similarity in the twin applications we submitted.¹⁹

3.5 Empirical Strategy

¹⁷ This platform is one of the biggest online recruitment websites. At present, the number of valid registered users exceeds 100 million, more than 5 million valid vacancies are posted on the website daily, and more than 40 million resumes a week are sent to enterprises via this recruitment platform.

¹⁸ Because some vacancies only accept applicants of one type of gender, only when a vacancy accepts applicants of both types of gender did we deliver at most four resumes. According to the relevant results of regressions and tests, which are available upon request, our results are not sensitive to this delivery strategy.

¹⁹ We consulted some human-resource experts of financial companies. According to them, one vacancy posted by big (small) companies receives about 200 (50) resumes. We only submitted two or four resumes to one vacancy. Thus, the signal-to-noise ratio is relatively high. We cannot completely rule out the possibility that some companies realized that we were delivering fake resumes, but the probability should be relatively small.

Our base regression equation is

$$(1) \quad \text{Callback}_{ij} = \beta \cdot \text{Look}_{ij} + \phi \cdot \text{Look}_{ij} \cdot X_{ij} + \varphi \cdot X_{ij} + \mu_j + e_{ij} + \eta_j + \varepsilon_{ij},$$

where for individual i ($i=1,2$) in pair j , Callback_{ij} denotes whether individual i receives an interview callback (1=callback received, 0 otherwise), Look_{ij} is the applicant's looks (1=attractive looks, 0 otherwise), X_{ij} is the vector of observed control variables of three types, including personal characteristics (e.g., gender and education), company features (e.g., location city, ownership, listed status, and business mode), and vacancy features (e.g., dummy variable for research position and dummy variable for high payment position). μ_j represents other observed relevant variables that could vary across pairs but not within pairs, such as city FE. e_{ij} and η_j respectively denote the unobserved variables that vary by person and by pair, primarily resume features and delivery characteristics, which could be observed in resumes and during the delivery process but were not encoded. ε_{ij} represents the disturbance term. To analyze the interaction effects of appearance with other attributes (such as gender, education, company features, and position features), we introduce interaction terms between the looks dummy and other explanatory variables of interest (e.g., $\text{Look}_{ij} \cdot X_{ij}$).

Since our encoding cannot control for all characteristics coming from resumes or delivery processes, estimates based on Equation (1) could be biased. By using a within-pairs FE model, we can eliminate both observed and unobserved within-pairs effects (i.e., μ_j and η_j). Additionally, according to the experimental design, since other unobserved personal features are almost the same within pairs, e_{ij} can be removed. Therefore, we obtain a refined FE estimate in equation (2):

$$(2) \quad \begin{aligned} \text{Callback}_{1j} - \text{Callback}_{2j} = & \beta \cdot (\text{Look}_{1j} - \text{Look}_{2j}) + \phi \cdot (\text{Look}_{1j} \cdot X_{1j} - \text{Look}_{2j} \cdot X_{2j}) \\ & + \varphi \cdot (X_{1j} - X_{2j}) + (\varepsilon_{1j} - \varepsilon_{2j}). \end{aligned}$$

Utilizing the experimental data, we estimate the beauty premium with this pair FE model.²⁰

²⁰ We also estimated the ordinary least squares (OLS) regressions without the pair fixed effects but with robust

We also include individual, company, and vacancy FEs. Additionally, heterogeneous appearance discriminations across gender, education, company features, and position types are explored.

4 Results and Discussion

4.1 Summary Statistics

Table 1 presents the summary statistics in terms of the relative frequency of being called for an interview in different subsamples. Not surprisingly, the data suggest appearance discrimination in the labor market. Attractive individuals are 5.6 percentage points more likely to be called for an interview, as indicated by their callback relative frequencies (0.389 for attractive applicants (B) vs. 0.333 for ordinary looking applicants (O)). Appearance discrimination or the beauty premium, indicated by the magnitude of difference between B and O (Diff (B-O)), seems slightly more serious among women (5.7 percentage points for women vs. 5.4 percentage points for men), but the difference in the beauty premium between men and women is insignificant (shown in Diff (M-F)).

[Insert Table 1 Here]

Table 1 then reports callback rates for the four educational credentials mentioned in Section 3.3: low-quality, middle-quality, and high-quality bachelor's degrees, and high-quality master's degrees. On the whole, attractive individuals are more likely to be called for an interview across all education levels. Having better educational credentials (e.g., upgrading from a low-quality bachelor's to a high-quality bachelor's degree, or from a middle-quality bachelor's to a high-quality master's degree) generally reduces appearance discrimination for the whole sample, indicated by a smaller magnitude in Diff (B-O). Intriguingly, there are heterogeneous effects between men and women across education levels. As reported in the last column, low-education-level (e.g., low-quality and middle-quality bachelor's degrees) men seem to suffer more serious appearance discrimination than women (Diff (M-F) being positive), but high-education-level (e.g., high-quality bachelor's and master's degrees) men are less likely to encounter appearance discrimination than women (Diff (M-F) being negative). However, the

standard errors clustered at the individual level. The results of these OLS regressions are presented in the appendices (e.g., Table A1-A5 and C1-C5).

difference between women and men in appearance discrimination is significant only for low-quality bachelor's degrees.

Callback rates can also be stratified by different employer features. First, although the first-tier cities have more vacancies, our experimental applicants on average received fewer interview in those cities than they did in second-tier cities, maybe due to more intensive competition in first-tier cities' labor markets. Appearance discrimination was worse in first-tier cities than in second-tier cities, especially for women (Diff (B-O) is 6.4 percentage points and 4.4 percentage points for first- and second-tier cities, respectively). Second, listed companies are generally more likely to discriminate against ordinary-looking applicants, in particular among women (Diff (B-O) is 5.5 percentage points in non-listed companies and 7.5 percentage points in the listed companies). Third, compared with "other" ownership firms such as state-owned enterprises and foreign firms, private companies exhibit more discrimination against ordinary-looking applicants, indicated by a positive and significant Diff (B-O). Fourth, Internet-based financial firms seem less likely than other types of companies to discriminate against female applicants with ordinary looks.

Finally, we turn to callback rates by vacancy features. We classified the jobs to be either research or sales, and either high-payment type or not. Regardless of classification, beauty premiums in interview opportunities are observed in the whole sample, female subsample, and male subsample. Research-type vacancies exhibit larger beauty premiums (indicated by the Diff (B-O) estimates)) than sales positions for the male subsample, but not for the female subsample. The beauty premium is larger for high-payment positions in the whole sample and male subsample, but slightly smaller for the female subsample.²¹

We next turn to our FE regression estimates of appearance discrimination. As with the summary statistics, we first examine differences by gender and then by education, employer attributes, and job features.

4.2 By Gender

The existing literature documents gender differences in the beauty premium (Heilman and

²¹ However, the differences in beauty premium by employer features and vacancy features all are insignificant. The relevant test results are available upon request.

Saruwatari, 1979; Hamermesh and Biddle, 1994; Patacchini et al., 2015). However, we do not find evidence of a gender difference in appearance discrimination in callback rates. Table 2 reports baseline results from a FE estimation based on equation (2). The results indicate that the callback rate is 5.6 percentage points higher for resumes with attractive ID photos. This estimate, which controls for a wide variety of factors including the pair FEs, is the same as the raw difference in Table 1. The estimate of appearance discrimination, indicated by the *Look* coefficient, is strongly significant and almost identical for men and women.

[Insert Table 2 Here]

For the whole sample, the coefficient for the interaction term *Look_Male*, reflecting gender differences in appearance discrimination, is insignificant after accounting for individual FE and the other controls.²² This result is consistent with the summary statistics (see Diff (M-F) estimates at Row 1 in Table 1). Meanwhile, comparing the key estimate between the male and female subsamples, the situation is slightly worse for women but the difference between the two coefficients is statistically insignificant, as reported in Column 5. People usually think that women encounter much stronger appearance discrimination in the labor market, consistent with the findings of most existing studies. We do not observe a significant difference in the beauty premium for men versus women here. Different results may occur in different contexts, including different countries or different jobs. Another potential explanation is that the finding of a gender difference in previous studies is due to omitted variable bias or measurement error bias.

4.3 By Education

Physical appearance partially influences human capital formation and can function as a signal in the labor market (Mocan and Tekin, 2010; Von Bose, 2013). We next examine whether appearance discrimination is alleviated or amplified by better educational credentials.

In Panel A of Table 3, the coefficient of the interaction term *Look_Education*, where *Education* is an ordinal variable (1: low-quality bachelor; 2: middle-quality bachelor; 3: high-quality bachelor; 4: high-quality master), captures the effect of education on appearance

²² The OLS estimate of *Look_Male* in Table A1 is statistically significant, in contrast.

discrimination. Its estimates in the whole sample imply that improving educational credentials could reduce the probability of encountering appearance discrimination by 0.7 percentage points. Comparing results from female and male subsamples, we find that education influences appearance discrimination very differently, -0.024 for men and 0.011 for women, and the difference (Diff (M vs. F)) is highly significant. Thus, the mitigating role of education on appearance discrimination only exists among men, while ordinary-looking women with better educational quality are more likely to encounter appearance discrimination.²³ Panels B to E in Table 3 give the results of regressions for different subsamples with different diplomas. For the low-quality bachelor's degrees, men face significantly more serious appearance discrimination than women (the *Look* coefficient is 0.193 for men vs. 0.043 for women). However, for high-quality master's degrees, appearance discrimination is more serious for women than for men (the *Look* coefficient is 0.032 for men vs. 0.066 for women). The gender difference in the beauty premium is insignificant for middle-quality or high-quality bachelor's degrees. It implies that there is a diverse pattern in terms of the beauty premium between men and women. Men with the weakest educational credential in our sample (low-quality bachelor's degrees) and women with the best educational credential (high-quality master's degrees in this case) encounter the most appearance discrimination.

[Insert Table 3 Here]

We further investigate whether having better credentials could alleviate appearance discrimination. For applicants with low-quality bachelor's degrees, ordinary-looking men could significantly increase the probability of receiving interview by instead graduating from a middle- or high-quality university or earning a high-quality master's degree, as indicated by the p-values of the test results conducted in Diff (B vs. C), Diff (B vs. D), and Diff (B vs. E). For ordinary-looking men with middle-quality or high-quality bachelor's degrees, education advancement to a high-quality master's can, to some extent, mitigate appearance discrimination in the labor market (see Diff (C vs. E) and Diff (D vs. E)). However, ordinary-looking women with low-quality or middle-quality bachelor's degrees encounter even more serious appearance discrimination if they upgrade their education to a high-quality bachelor's/master's degree (see

²³ "Better education" in this context indicates having higher educational degrees or graduating from better universities.

Diff (B vs. E), Diff (C vs. D) and Diff (C vs. E)).

4.4 By Employer Attributes

We next explore potential heterogeneous appearance discrimination across employers in different locations, listed statuses, ownership, and transaction modes (whether transactions are completed mainly through the Internet or not). Results are reported in Table 4.

Location: First-Tier Cities vs. Second-Tier Cities—Considering that the level of regional economic development has important effects on employment, we examine the influence of company location on appearance discrimination. Estimates of the coefficient of the interaction term *Look_BigCity* in Panel A suggest that, in the whole sample and male subsample, the company's location does not impact appearance discrimination in terms of receiving interview. However, women in the labor markets of first-tier cities encounter much stronger appearance discrimination than those in second-tier cities, and the difference in the coefficients is significant. There are more women than men in big cities worldwide because big cities have better job opportunities and better marriage markets (Edlund, 2005). It is possible that attractive women are more likely to be favored in more competitive markets. Thus, attractive women can receive a higher premium in big cities.

[Insert Table 4 Here]

Listed Status: Listed vs. Non-Listed—Commonly, listed companies are more concerned about legal provisions, public opinion, and public image, which might influence their recruitment practices. As presented in Panel B, listed companies indeed favor good-looking applicants more than non-listed companies (the coefficient for *Look* is 0.067 for the listed companies (B2) vs. 0.054 for the non-listed companies (B3)), in particular for women (0.075 for the listed companies vs. 0.055 for the non-listed companies). Furthermore, we test the difference in the *Look* coefficients between the B2 and B3 subsamples using Diff (B2 vs. B3). The results suggest that women significantly encounter more serious appearance discrimination in listed companies than in non-listed companies, and the difference is significant at the 10% significance level.

Ownership: Private vs. Others—Ownership could also influence appearance discrimination. State-owned enterprises (SOE) bear more social responsibility and are more

involved with policy implementation. In addition, foreign companies generally are regulated by domestic as well as international laws and are more strictly supervised by the host government, while private firms are relatively less regulated. Theoretically, the former two enjoy better resources for promoting their public images, while private entrepreneurs depend more on employee performance. Even though the *Look* coefficients are each significant in the Panel C2 (private companies) and Panel C3 (non-private companies), their difference (Diff C2 vs. C3) is not significant. Furthermore, the coefficient of the interaction term (*Look_Private*) is also not significant.²⁴ We infer that appearance discrimination is independent of the company ownership structure; thus, the difference in appearance discrimination across different ownership companies observed could be attributable to individual unobserved idiosyncrasies.

Transaction Mode: Internet vs. Others—Traditional financial firms usually conduct business on a face-to-face basis, while Internet financial companies usually complete transactions through networks. Thus, employees' appearance could be more important for traditional financial companies. However, as reported in Panel D1 of Table 4, all the coefficients of the interaction term *Look_Internet* are insignificant in the FE estimations. The test for the difference in the *Look* coefficients in Panel D2 (Internet financial companies) and Panel D3 (other companies) subsamples (Diff (D2 vs. D3)) also suggest no significant difference in appearance discrimination between Internet-based firms and other types of companies.²⁵ Therefore, we do not observe a significant difference in appearance discrimination across transaction modes.

4.5 By Job Features

For an employer, a well-placed good-looking employee potentially has two types of positive effects on firm value: one is internal and stimulates other employees to work hard, and another is external and enhances the enterprise's image and economic profit. We therefore investigate

²⁴ The OLS estimates of *Look_Private* in Table A3 show that private firms are less likely to discriminate with respect to ordinary men, but are more likely to prefer good-looking women, while other firms (i.e., foreign firms and SOEs) are more likely to discriminate with respect to ordinary-looking women.

²⁵ Results of the OLS estimations in Panel D of Table A3 suggest that the coefficient of the interaction term *Look_Internet* is significantly positive (negative) for male (female subsample) which infers that compared with other financial firms, Internet-based firms are more (less) likely to discriminate against ordinary-looking men (women).

the heterogeneous beauty premium by position features. Table 5 provides the estimation results.

[Insert Table 5 Here]

Research vs. Sales Vacancies—We divide positions into two categories: research-intensive and sales-intensive positions. In general, the sales-intensive positions require better looks because these jobs require direct communication with consumers and quality and output depend on consumers' impressions. It is reasonable to expect that attractive candidates are more likely to receive an interview when applying for sales-intensive positions than when applying for research-intensive positions. However, as shown in Table 5, this expectation is weakly tenable only for female samples, indicated by a negative but insignificant sign of *Look_Research* coefficient.²⁶ Men who apply for research rather than sales jobs will suffer significantly more serious appearance discrimination (the coefficient for *Look* is 0.063 in the research-intensive positions vs. 0.043 in the sales-intensive positions). One potential interpretation is that the labor market for research vacancies is male-dominated and strong competition possibly increases the beauty premium for men.

Education Requirement and Payment—We classify positions into two types: one asks for candidates with better educational quality and correspondingly provides higher pay (HH, or high education and high payment); the other requires relatively lower educational attainment and offers lower pay (LL, or low education and low payment).²⁷ As reported in Table 5, estimates of interaction terms from the FE regressions indicate that men who apply for the HH position encounter more serious appearance discrimination. The results of stratified subsamples also confirm this point (the coefficient for *Look* is 0.064 in the HH subsample vs. 0.043 in the LL subsample), and the difference is statistically significant. At the same time, ordinary-looking women will not face appearance discrimination when applying for the HH positions according to the OLS estimations (see Table A4), but when we control for individual unobserved characteristics through FE estimations, the difference in the *Look* coefficients between the two types of positions subsamples disappears.

²⁶ The OLS results do indicate that males (females) are less (more) likely to suffer appearance discrimination when applying for sales-related jobs.

²⁷ Research positions generally require better education and provide higher payment than sales. Thus, these two dummies reflecting job features are highly correlated.

4.6 Robustness Checks

We further estimate the looks effect on performance in the labor market by including all interaction terms in the same regressions. The FE and OLS results reported in Table 6 and the Appendix (Tables A5, B5, and C5), respectively, are similar when we include all of the interactions or only one interaction term at a time. The FE estimates suggest that ordinary-looking individuals, especially men, can significantly alleviate the appearance discrimination by improving their educational credentials, while in first-tier cities, women suffer more serious appearance discrimination.

[Insert Table 6 Here]

The main estimation results presented here use a dummy variable to indicate which applicant in a pair is better looking. We estimated similar models using the linear value of the beauty score that we obtained through an online survey (see Section 2). The average value of the beauty score can capture the gap between two synthesized ID photos. Results that use the quantitative variable, *Beauty_Score*, are presented in the Appendix in Tables B1-B5 and C1-C5. The results are similar to the results using the dummy variable.

4.7 Addressing the Heckman Critique

Experimental audit and correspondence studies are two critical methods used to investigate discrimination in the labor market (Neumark, 2018). Correspondence studies address the criticisms of audit studies (i.e., applicants from different groups may not appear identical to employers) by delivering fictitious resumes that are basically identical across groups. Nevertheless, group differences in the variance of unobservable determinants of productivity can still generate spurious evidence of discrimination in either direction (Heckman and Siegelman, 1993). By applying the method developed by Neumark (2012), we address the Heckman critique and recover an unbiased estimate of discrimination.

Assume that productivity depends linearly and additively on two characteristics: X^I included on resumes and standardized to be X^{I*} across applicants in the study; and X^{II} , which is unobserved by firms. Let B and O respectively denote applicants with attractive and ordinary looks. Define γ as a term that reflects taste discrimination (undervaluation of

productivity) or statistical discrimination (an assumption that $E(X_B'') \neq E(X_O'')$) regarding looks. Assume that X_B'' and X_O'' are normally distributed, with zero means, and standard deviations σ_B'' and σ_O'' , respectively. Heckman's critique states that even if $E(X_B'') = E(X_O'')$, without proving $\sigma_B'' = \sigma_O''$, γ is unidentified. Following the procedure developed by Neumark et al. (2016), we use a heteroscedastic probit model to estimate γ . Table 7 shows the results. The heteroscedastic probit estimates are consistent with the probit estimates. Moreover, the ratio of attractive to ordinary applicants in the standard deviation of unobservables (i.e., σ_B'' / σ_O'') is extremely close to one (e.g., 0.999 in the male subsample). Further, given that the p-value equals 0.969 (0.346) in the male (female) subsample, we fail to reject the null hypothesis that $\sigma_B'' / \sigma_O'' = 1$. Therefore, our experimental evidence indicates that appearance discrimination is not just statistical discrimination and that taste-based discrimination indeed exists in the labor market, at least in the male subsample.

[Insert Table 7 Here]

5 Conclusions

It is easy to clearly legislate against discrimination by disabilities, race, or gender, but it is difficult to legislate against appearance discrimination because of the subtlety in establishing objective criteria on appearance. The beauty premium has been widely documented in existing literature. However, because of the problem of omitted variables, such as unobserved factors associated with productivity, it has been extremely difficult for previous studies to identify a causal relationship. In addition, most studies focus on measuring the impact of appearance discrimination on labor market outcomes through the wage gap. Considering appearance discrimination may also affect labor market opportunities, such as being selected to interview for a job, our study is intriguing and the results imply that plainer-looking men should try to go to better schools for winning interview opportunities.

This study employs a field experiment to provide new causal evidence on the existence of taste-based appearance discrimination at the pre-interview stage. In our experimental design,

we used resumes that differed in facial features but were otherwise basically identical and implemented a multi-layered stratified randomization delivery process. We were able to control for characteristics of employers, position features, and individual unobserved specifics and identify taste-based appearance discrimination in interview opportunities.

This study yields the following interesting findings. First, appearance discrimination results in unequal interview opportunities in the labor market, regardless of the scale of the market and the individual's gender or education; pure facial feature taste-based discrimination does exist. Second, having better educational credentials reduces observed discrimination. Third, when we analyze female and male subsamples separately, patterns of effects are different and heterogeneous. We observe that the gender difference in appearance discrimination becomes insignificant after accounting for unobserved characteristics through FE estimations; we also observe that education alleviates appearance discrimination, but differently across genders. Men can ease appearance discrimination in the employment market by improving their educational credentials, but women with better education are more likely to encounter appearance discrimination. Fourth, heterogeneous beauty premiums exist among different labor market scales, types of companies, and features of posted positions, although the evidence is weak for some cases. The results suggest that ordinary-looking applicants have more interview opportunities in second-tier cities.

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Table 1: Summary Statistics of Callbacks

	Dummy	Whole				Male (M)				Female (F)				DID
		B	O	Diff (B-O)	obs	B	O	Diff (B-O)	obs	B	O	Diff (B-O)	obs	Diff (M-F)
Whole		0.389	0.333	0.056***	9892	0.369	0.315	0.054***	4910	0.408	0.35	0.057***	4982	-0.003
Bach_Low	1	0.311	0.193	0.118***	560	0.35	0.157	0.193***	280	0.271	0.229	0.043	280	0.150**
Bach_Middle	1	0.374	0.332	0.042**	2792	0.346	0.302	0.044*	1462	0.405	0.364	0.041	1330	0.003
Bach_High	1	0.394	0.331	0.063***	3486	0.392	0.332	0.060**	1622	0.395	0.33	0.064***	1864	-0.004
Master_High	1	0.411	0.362	0.049***	3054	0.371	0.339	0.032	1546	0.452	0.386	0.066***	1508	-0.034
BigCity	0	0.502	0.453	0.049***	3464	0.487	0.433	0.054**	1780	0.519	0.475	0.044*	1684	0.01
	1	0.328	0.268	0.059***	6428	0.303	0.249	0.054***	3130	0.351	0.287	0.064***	3298	-0.01
Listed	0	0.387	0.333	0.054***	8580	0.367	0.313	0.053***	4264	0.407	0.353	0.055***	4316	-0.001
	1	0.399	0.332	0.067**	1312	0.387	0.328	0.059	646	0.411	0.336	0.075**	666	-0.016
Private	0	0.420	0.363	0.057	424	0.429	0.362	0.067	210	0.411	0.364	0.047	214	0.020
	1	0.387	0.332	0.055***	9468	0.367	0.313	0.054***	4700	0.408	0.35	0.058***	4768	-0.004
Internet	0	0.385	0.328	0.056***	8422	0.368	0.314	0.054***	4176	0.401	0.342	0.059***	4246	-0.005
	1	0.412	0.359	0.053**	1470	0.379	0.322	0.057	734	0.446	0.397	0.049	736	0.008
Research	0	0.359	0.308	0.051***	4530	0.335	0.292	0.043**	2262	0.384	0.325	0.059***	2268	-0.016
	1	0.414	0.354	0.060***	5362	0.399	0.335	0.063***	2648	0.428	0.372	0.056***	2714	0.007
High-Payment	0	0.360	0.309	0.051***	4570	0.333	0.29	0.043**	2284	0.387	0.327	0.059***	2286	-0.017
	1	0.414	0.354	0.060***	5322	0.401	0.337	0.064***	2626	0.426	0.37	0.056***	2696	0.008
Observations		4946	4946			2455	2455			2491	2491			

The first column is the value of the dummy variable. The value reported in addition to the first column is the mean of Callback (1 if receiving interview call, 0 otherwise). “B” and “O” respectively denote Attractive and Ordinary applicants. “obs” denotes Observations. Bach_Low, Bach_Middle, Bach_High, and Master_High equals 1 if the graduate respectively is as a low-quality bachelor, middle-quality bachelor, high-quality bachelor, and high-quality master, 0 otherwise. BigCity (1 if first-tier cities, 0 otherwise), Listed (1 if listed, 0 otherwise), Private (1 if private companies, 0 otherwise), Internet (1 if Internet Financial Companies, 0 otherwise), Research (1 if research position, 0 otherwise), and High-Payment (1 if High Education and High Payment position, 0 otherwise) are dummies. Diff (B-O): the mean difference between B and O. Diff (M-F): the difference between males and females in Diff (B-O). ***p<0.01; **p<0.05; *p<0.1.

Table 2: Look and Callback by Gender: Fixed Effect Estimation

	Whole				Male (M)		Female (F)		Diff (M vs. F)
	(1)		(2)		(3)		(4)		(5)
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	p-value
Look	0.056***	(0.003)	0.057***	(0.005)	0.054***	(0.005)	0.057***	(0.005)	0.485
Look_Male			-0.003	(0.007)					

Dependent Variable (Callback: 1 if receiving interview call, 0 otherwise), Look (1 if attractive, 0 otherwise), and Male (1 if male, 0 otherwise) are dummies. Diff (M vs. F) reports the test result of hypothesis: the coefficient of male subsample equals that of female subsample. Standard errors (SE) in parentheses are robust to heteroscedasticity. All regressions are fixed effect estimations and control for city, city level, company type, ownership type of company, listed dummy, application position type, research dummy, and requirements of application position. ***p<0.01; **p<0.05; *p<0.1.

Table 3: Look and Callback by Education: Fixed Effect Estimation

	Whole		Male (M)		Female (F)		Diff (M vs. F)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	p-value
<i>Panel A: Whole</i>								
Look	0.075***	(0.012)	0.123***	(0.019)	0.025*	(0.015)		0.000
Look_Education	-0.007*	(0.004)	-0.024***	(0.006)	0.011**	(0.005)		0.000
<i>Panel B: Low-Quality Bachelor (Education=1)</i>								
Look	0.118***	(0.019)	0.193***	(0.034)	0.043**	(0.017)		0.000
<i>Panel C: Middle-Quality Bachelor (Education=2)</i>								
Look	0.042***	(0.005)	0.044***	(0.008)	0.041***	(0.008)		0.683
<i>Panel D: High-Quality Bachelor (Education=3)</i>								
Look	0.063***	(0.006)	0.060***	(0.008)	0.064***	(0.008)		0.630
<i>Panel E: High-Quality Master (Education=4)</i>								
Look	0.049***	(0.006)	0.032***	(0.006)	0.066***	(0.009)		0.000
Diff (B vs. C)	0.000		0.000		0.866			
Diff (B vs. D)	0.000		0.000		0.108			
Diff (B vs. E)	0.000		0.000		0.087			
Diff (C vs. D)	0.000		0.037		0.003			
Diff (C vs. E)	0.213		0.102		0.003			
Diff (D vs. E)	0.018		0.000		0.821			

Dependent Variable (Callback: 1 if receiving interview call, 0 otherwise) and Look (1 if attractive, 0 otherwise) are dummies. Education is an ordinal variable (1: low-quality bachelor; 2: middle-quality bachelor; 3: high-quality bachelor; 4: high-quality master). Diff (M vs. F) reports the test result of hypothesis: the coefficient of male subsample equals that of female subsample. Diff (X vs. Y) reports the test result (p-value) of hypothesis: the coefficient of Panel X equals that of Panel Y. Standard errors (SE) in parentheses are robust to heteroscedasticity. All regressions are fixed effect estimations and control for city, city level, company type, ownership type of company, listed dummy, application position type, research dummy, and requirements of application position. ***p<0.01; **p<0.05; *p<0.1.

Table 4: Look and Callback by Employers Attributes: Fixed Effect Estimation

	Whole		Male (M)		Female (F)		Diff (M vs. F)
	(1)		(2)		(3)		(4)
	Coeff.	SE	Coeff.	SE	Coeff.	SE	p-value
<i>Panel A1: City Level</i>							
Look	0.049***	(0.005)	0.054***	(0.008)	0.044***	(0.007)	0.173
Look_BigCity	0.010	(0.007)	0.000	(0.009)	0.020**	(0.009)	0.034
<i>Panel A2: First-Tier Cities (BigCity=1)</i>							
Look	0.059***	(0.004)	0.054***	(0.006)	0.064***	(0.006)	0.092
<i>Panel A3: Second-Tier Cities (BigCity=0)</i>							
Look	0.049***	(0.005)	0.054***	(0.008)	0.044***	(0.007)	0.173
Diff (A2 vs. A3)	0.028		0.955		0.002		
<i>Panel B1: Listed Status</i>							
Look	0.054***	(0.003)	0.053***	(0.005)	0.055***	(0.005)	0.805
Look_Listed	0.013	(0.010)	0.005	(0.014)	0.020	(0.015)	0.304
<i>Panel B2: Listed Companies (Listed=1)</i>							
Look	0.067***	(0.010)	0.059***	(0.013)	0.075***	(0.014)	0.239
<i>Panel B3: Non-Listed Companies (Listed=0)</i>							
Look	0.054***	(0.003)	0.053***	(0.005)	0.055***	(0.005)	0.805
Diff (B2 vs. B3)	0.076		0.588		0.059		
<i>Panel C1: Company Ownership</i>							
Look	0.057***	(0.016)	0.067***	(0.024)	0.047**	(0.020)	0.3747
Look_Private	-0.001	(0.016)	-0.013	(0.025)	0.011	(0.021)	0.2916
<i>Panel C2: Private Companies (Private=1)</i>							
Look	0.056***	(0.003)	0.054***	(0.005)	0.058***	(0.005)	0.367
<i>Panel C3: Non-Private Companies (Private=0)</i>							
Look	0.057***	(0.016)	0.067***	(0.025)	0.047**	(0.021)	0.375
Diff (C2 vs. C3)	0.613		0.457		0.452		
<i>Panel D1: Company Industry</i>							
Look	0.056***	(0.004)	0.054***	(0.005)	0.059***	(0.005)	0.299
Look_Internet	-0.003	(0.009)	0.004	(0.013)	-0.010	(0.012)	0.287
<i>Panel D2: Internet Financial Companies (Internet=1)</i>							
Look	0.053***	(0.008)	0.057***	(0.012)	0.049***	(0.011)	0.478
<i>Panel D3: Other Companies (Internet=0)</i>							
Look	0.056***	(0.004)	0.054***	(0.005)	0.059***	(0.005)	0.299
Diff (D2 vs. D3)	0.613		0.699		0.255		

Dependent Variable (Callback: 1 if receiving interview call, 0 otherwise) and Look (1 if attractive, 0 otherwise) are dummies. Diff (M vs. F) reports the test result of hypothesis: the coefficient of male subsample equals that of female subsample. Diff (X vs. Y) reports the test result (p-value) of hypothesis: the coefficient of Panel X equals that of Panel Y. Standard errors (SE) in parentheses are robust to heteroscedasticity. All regressions are fixed effect estimations and control for city, city level, company type, ownership type of company, listed dummy, application position type, research dummy, and requirements of application position. ***p<0.01; **p<0.05; *p<0.1.

Table 5: Look and Callback by Job Features: Fixed Effect Estimation

	Whole		Male (M)		Female (F)		Diff (M vs. F)
	(1)		(2)		(3)		(4)
	Coeff.	SE	Coeff.	SE	Coeff.	SE	p-value
<i>Panel A1: Research vs. Sales Vacancies</i>							
Look	0.051***	(0.005)	0.043***	(0.006)	0.059***	(0.007)	0.017
Look_Research	0.008	(0.007)	0.020**	(0.009)	-0.003	(0.009)	0.012
<i>Panel A2: Research (Research=1)</i>							
Look	0.060***	(0.005)	0.063***	(0.007)	0.056***	(0.006)	0.251
<i>Panel A3: Sale (Research=0)</i>							
Look	0.051***	(0.005)	0.043***	(0.006)	0.059***	(0.007)	0.017
Diff (A2 vs. A3)	0.067		0.002		0.646		
<i>Panel B1: Education Requirement and Payment</i>							
Look	0.051***	(0.005)	0.043***	(0.006)	0.059***	(0.007)	0.012
Look_High-Payment	0.009	(0.007)	0.021**	(0.009)	-0.004	(0.009)	0.007
<i>Panel B2: High Education and High Payment (High-Payment=1)</i>							
Look	0.060***	(0.005)	0.064***	(0.007)	0.056***	(0.006)	0.200
<i>Panel B3: Low Education and Low Payment (High-Payment=0)</i>							
Look	0.051***	(0.005)	0.043***	(0.006)	0.059***	(0.007)	0.012
Diff (B2 vs. B3)	0.065		0.001		0.564		

Dependent Variable (Callback: 1 if receiving interview call, 0 otherwise) and Look (1 if attractive, 0 otherwise) are dummies. Diff (M vs. F) reports the test result of hypothesis: the coefficient of male subsample equals that of females subsample. Diff (X vs. Y) reports the test result (p-value) of hypothesis: the coefficient of Panel X equals that of Panel Y. Standard errors (SE) in parentheses are robust to heteroscedasticity. All regressions are fixed effect estimations and control for city, city level, company type, ownership type of company, listed dummy, application position type, research dummy, and requirements of application position. ***p<0.01; **p<0.05; *p<0.1.

Table 6: Look and Callback: Fixed Effect Estimation Including All Interaction Terms

	Whole		Male (M)		Female (F)		Diff (M vs. F)
	(1)		(2)		(3)		(4)
	Coeff.	SE	Coeff.	SE	Coeff.	SE	p-value
Look	0.102***	(0.026)	0.194***	(0.042)	0.009	(0.030)	0.000
Look_Male	-0.002	(0.007)					
Look_Bach_Middle	-0.074***	(0.020)	-0.147***	(0.034)	-0.001	(0.019)	0.000
Look_Bach_High	-0.053***	(0.020)	-0.130***	(0.035)	0.024	(0.020)	0.000
Look_Master_High	-0.067***	(0.020)	-0.158***	(0.034)	0.025	(0.020)	0.000
Look_BigCity	0.010	(0.007)	-0.001	(0.010)	0.021**	(0.009)	0.021
Look_Listed	0.013	(0.011)	0.005	(0.015)	0.020	(0.016)	0.324
Look_Private	0.004	(0.017)	-0.007	(0.026)	0.016	(0.022)	0.320
Look_Internet	0.001	(0.009)	0.009	(0.013)	-0.008	(0.013)	0.193
Look_Research	0.004	(0.007)	0.005	(0.009)	0.002	(0.010)	0.758
Observations	9,892		4,910		4,982		
R ²	0.062		0.079		0.062		

Dependent Variable (Callback: 1 if receiving interview call, 0 otherwise), Look (1 if attractive, 0 otherwise), and Male (1 if male, 0 otherwise) are dummies. Bach_Low, Bach_Middle, Bach_High, and Master_High equals 1 if one is the graduate respectively as a low-quality bachelor, middle-quality bachelor, high-quality bachelor, and high-quality master, 0 otherwise. BigCity (1 if first-tier cities, 0 otherwise), Listed (1 if listed, 0 otherwise), Private (1 if private companies, 0 otherwise), Internet (1 if Internet Financial Companies, 0 otherwise) and Research (1 if research position, 0 otherwise) are dummies. Standard errors (SE) in parentheses are robust to heteroscedasticity. All regressions are fixed effect estimations and control for city, city level, company type, ownership type of company, listed dummy, application position type, research dummy, and requirements of application position. ***p<0.01; **p<0.05; *p<0.1.

Table 7: Look and Callback: Heteroscedastic Probit Estimation (Corrects for Potential Biases from Difference in Variance of Unobservables)

	Whole	Male	Female
	(1)	(3)	(5)
<i>Panel A: Probit Estimates</i>			
Look (Marginal)	0.060*** (0.000)	0.059*** (0.000)	0.062*** (0.000)
<i>Panel B: Heteroscedastic Probit Estimates</i>			
Look (Marginal)	0.060*** (0.004)	0.059*** (0.005)	0.062*** (0.005)
Standard Deviation of Unobservables, Attractive/Ordinary	1.017	0.999	1.039
Test: Ratio of Standard Deviations = 1 (p-value)	0.498	0.969	0.346
Observations	9,880	4,902	4,974

Dependent Variable (Callback: 1 if receiving interview call, 0 otherwise) and Look (1 if attractive, 0 otherwise) are dummies. Marginal effects computed as the change in the probability associated with “Look,” using the continuous approximation, evaluating other variables at their means; the continuous approximation yields an unambiguous decomposition of the heteroscedastic Probit estimates. p-values are based on Wald tests. ***p<0.01; **p<0.05; *p<0.1.

APPENDIX

APPENDIX 1: THE BASIC LAYOUT OF RESUME TEMPLATE

Name				
Gender				Photo
Phone		Email		
Address				
Education				
2012/09-2016/07	University	Major	Academic-Degree	
Major Courses		Course Name		
Honors		Scholarship		
Internship Experience				
2015/07-2015/09	Bank / Securities			Department
Job Content				
Practice Experience				
2012/09-2016/09	Employer			Department
Job Content				
Occupation's Skills				
Major's Skills				
Securities / Bank / Accounting				
Language Skills				
Pass College English Level 6, and has a good command of English in listening, speaking, reading, writing and translation ability				
IT Skills				
Good command of office software/ C / Python / R / Java				

APPENDIX 2: DESCRIPTION OF INFORMATION TYPE IN RESUME

Information Type	Description
Abroad Study Experience	Whether an individual has short experience in going abroad to study
Scholarship	Whether an individual has received scholarship, including international, national, provincial, and university scholarships
Internship Experience	Whether an individual has internship experience, including experience in companies, governments, or organizations with the same specialties as samples
Research Experience	Whether an individual has scientific research experience, including project, patent, above academic paper , and major tournament
Practical Experience	Whether an individual has practical experience, including student activities, association activities, volunteering, and other social activities
CET-4	Whether an individual has passed CET-4, with the score above 425
CET-6	Whether an individual has passed CET-6, with the score above 425
Examination for Going Abroad	Whether an individual has taken and passed various examinations for going abroad, such as GRE, GMAT, TOEFL, IELTS, and so on
Other Foreign Language Skills	Whether an individual has second foreign language skills, including Japanese, German, French, Korean, and so on
Office Software	Whether an individual is skilled to use Office software
Computer Language	Whether an individual is skilled to use computer programming language, including C language, Java, R language, Python, Matlab, SQL, and so on
Statistical Software	Whether an individual is skilled to use statistical software, such as SPSS, Eviews, Stata, SAS, and so on
Professional Certificate	Whether an individual has any professional certificate related to his/her major, including accounting qualification certificate, bank qualification certificate, security practice qualification certificate, and so on
Higher Professional Certificate	Whether an individual has higher professional certificate related to his/her own specialties, such as CFA, FRM, certified public accountant, certified tax agent, and so on

Notes. – CET denotes College English Test.

APPENDIX 3: ID PHOTO



Figure 1a Attractive Woman



Figure 1b Ordinary Woman



Figure 2a Attractive Man



Figure 2b Ordinary Man

APPENDIX 4: TABLES

Table A1: Look and Callback by Gender: OLS Estimation

	Whole		Male (M)		Female (F)	
	(1)	(2)	(3)	(4)	(5)	(6)
	Coeff.	SE	Coeff.	SE	Coeff.	SE
Look	0.056***	(0.000)	0.057***	(0.000)	0.054***	(0.000)
Look_Male			-0.003***	(0.000)		

Dependent Variable (Callback: 1 if receiving interview call, 0 otherwise), Look (1 if attractive, 0 otherwise), and Male (1 if male, 0 otherwise) are dummies. Robust standard errors (SE) are in parentheses, clustered at the resumes pair are in parentheses. All regressions are OLS estimations and control for city, city level, company type, ownership type of company, listed dummy, application position type, research dummy, and requirements of application position. ***p<0.01; **p<0.05; *p<0.1.

Table A2: Look and Callback by Education: OLS Estimation

	Whole		Male (M)		Female (F)	
	(1)	(2)	(3)	(4)	(5)	(6)
	Coeff.	SE	Coeff.	SE	Coeff.	SE
<i>Panel A: Whole</i>						
Look	0.075***	(0.000)	0.123***	(0.000)	0.025***	(0.000)
Look_Education	-0.007***	(0.000)	-0.024***	(0.000)	0.011***	(0.000)
<i>Panel B: Low-Quality Bachelor (Education=1)</i>						
Look	0.118***	(0.000)	0.193***	(0.000)	0.043***	(0.000)
<i>Panel C: Middle-Quality Bachelor (Education=2)</i>						
Look	0.042***	(0.000)	0.044***	(0.000)	0.041***	(0.000)
<i>Panel D: High-Quality Bachelor (Education=3)</i>						
Look	0.063***	(0.000)	0.060***	(0.000)	0.064***	(0.000)
<i>Panel E: High-Quality Master (Education=4)</i>						
Look	0.049***	(0.000)	0.032***	(0.000)	0.066***	(0.000)

Dependent Variable (Callback: 1 if receiving interview call, 0 otherwise) and Look (1 if attractive, 0 otherwise) are dummies. Education is an ordinal variable (1: low-quality bachelor; 2: middle-quality bachelor; 3: high-quality bachelor; 4: high-quality master). Robust standard errors (SE) are in parentheses, clustered at the resumes pair are in parentheses. All regressions are OLS estimations and control for city, city level, company type, ownership type of company, listed dummy, application position type, research dummy, and requirements of application position. ***p<0.01; **p<0.05; *p<0.1.

Table A3: Look and Callback by Employers Attributes: OLS Estimation

	Whole		Male (M)		Female (F)	
	(1)		(2)		(3)	
	Coeff.	SE	Coeff.	SE	Coeff.	SE
<i>Panel A1: City Level</i>						
Look	0.049***	(0.000)	0.054***	(0.000)	0.044***	(0.000)
Look_BigCity	0.010***	(0.000)	0.000***	(0.000)	0.020***	(0.000)
<i>Panel A2: First-Tier Cities (BigCity=1)</i>						
Look	0.059***	(0.000)	0.054***	(0.000)	0.064***	(0.000)
<i>Panel A3: Second-Tier Cities (BigCity=0)</i>						
Look	0.049***	(0.000)	0.054***	(0.000)	0.044***	(0.000)
<i>Panel B1: Listed Status</i>						
Look	0.054***	(0.000)	0.053***	(0.000)	0.055***	(0.000)
Look_Listed	0.013***	(0.000)	0.005***	(0.000)	0.020***	(0.000)
<i>Panel B2: Listed Companies (Listed=1)</i>						
Look	0.067***	(0.000)	0.059***	(0.000)	0.075***	(0.000)
<i>Panel B3: Non-Listed Companies (Listed=0)</i>						
Look	0.054***	(0.000)	0.053***	(0.000)	0.055***	(0.000)
<i>Panel C1: Company Ownership</i>						
Look	0.057***	(0.000)	0.067***	(0.000)	0.047***	(0.000)
Look_Private	-0.001***	(0.000)	-0.013***	(0.000)	0.011***	(0.000)
<i>Panel C2: Private Companies (Private=1)</i>						
Look	0.056***	(0.000)	0.054***	(0.000)	0.058***	(0.000)
<i>Panel C3: Non-Private Companies (Private=0)</i>						
Look	0.057***	(0.000)	0.067***	(0.000)	0.047***	(0.000)
<i>Panel D1: Company Industry</i>						
Look	0.056***	(0.000)	0.054***	(0.000)	0.059***	(0.000)
Look_Internet	-0.003***	(0.000)	0.004***	(0.000)	-0.010***	(0.000)
<i>Panel D2: Internet Financial Companies (Internet=1)</i>						
Look	0.053***	(0.000)	0.057***	(0.000)	0.049***	(0.000)
<i>Panel D3: Other Companies (Internet=0)</i>						
Look	0.056***	(0.000)	0.054***	(0.000)	0.059***	(0.000)

Dependent Variable (Callback: 1 if receiving interview call, 0 otherwise) and Look (1 if attractive, 0 otherwise) are dummies. Robust standard errors (SE) are in parentheses, clustered at the resumes pair are in parentheses. All regressions are OLS estimations and control for city, city level, company type, ownership type of company, listed dummy, application position type, research dummy, and requirements of application position. ***p<0.01; **p<0.05; *p<0.1.

Table A4: Look and Callback by Job Features: OLS Estimation

	Whole		Male (M)		Female (F)	
	(1)		(2)		(3)	
	Coeff.	SE	Coeff.	SE	Coeff.	SE
<i>Panel A1: Research vs. Sales Vacancies</i>						
Look	0.051***	(0.000)	0.043***	(0.000)	0.059***	(0.000)
Look_Research	0.008***	(0.000)	0.020***	(0.000)	-0.003***	(0.000)
<i>Panel A2: Research (Research=1)</i>						
Look	0.060***	(0.000)	0.063***	(0.000)	0.056***	(0.000)
<i>Panel A3: Sale (Research=0)</i>						
Look	0.051***	(0.000)	0.043***	(0.000)	0.059***	(0.000)
<i>Panel B1: Education Requirement and Payment</i>						
Look	0.051***	(0.000)	0.043***	(0.000)	0.059***	(0.000)
Look_High-Payment	0.009***	(0.000)	0.021***	(0.000)	-0.004***	(0.000)
<i>Panel B2: High Education and High Payment (High-Payment=1)</i>						
Look	0.060***	(0.000)	0.064***	(0.000)	0.056***	(0.000)
<i>Panel B3: Low Education and Low Payment (High-Payment=0)</i>						
Look	0.051***	(0.000)	0.043***	(0.000)	0.059***	(0.000)

Dependent Variable (Callback: 1 if receiving interview call, 0 otherwise) and Look (1 if attractive, 0 otherwise) are dummies. Robust standard errors (SE) are in parentheses, clustered at the resumes pair are in parentheses. All regressions are OLS estimations and control for city, city level, company type, ownership type of company, listed dummy, application position type, research dummy, and requirements of application position. ***p<0.01; **p<0.05; *p<0.1.

Table A5: Look and Callback: OLS Estimation Including All Interaction Terms

	Whole		Male (M)		Female (F)	
	(1)		(2)		(3)	
	Coeff.	SE	Coeff.	SE	Coeff.	SE
Look	0.012*	(0.001)	0.087***	(0.000)	-0.063**	(0.003)
Look_Male	-0.003***	(0.000)				
Look_Bach_Middle	0.044**	(0.002)	-0.022**	(0.000)	0.108**	(0.004)
Look_Bach_High	0.031**	(0.001)	-0.017***	(0.000)	0.078**	(0.003)
Look_Master_High	0.018**	(0.001)	-0.070***	(0.000)	0.104**	(0.003)
Look_BigCity	0.011***	(0.000)	0.002***	(0.000)	0.018***	(0.000)
Look_Listed	0.013***	(0.000)	0.005***	(0.000)	0.020***	(0.000)
Look_Private	0.002***	(0.000)	-0.011***	(0.000)	0.016***	(0.000)
Look_Internet	-0.002**	(0.000)	0.006***	(0.000)	-0.011***	(0.000)
Look_Research	0.011***	(0.000)	0.016***	(0.000)	0.005**	(0.000)
Observations	9,892		4,910		4,982	
R ²	0.062		0.079		0.062	

Dependent Variable (Callback: 1 if receiving interview call, 0 otherwise), Look (1 if attractive, 0 otherwise), and Male (1 if male, 0 otherwise) are dummies. Bach_Low, Bach_Middle, Bach_High, and Master_High equals 1 if one is the graduate respectively as a low-quality bachelor, middle-quality bachelor, high-quality bachelor, and high-quality master, 0 otherwise. BigCity (1 if first-tier cities, 0 otherwise), Listed (1 if listed, 0 otherwise), Private (1 if private companies, 0 otherwise), Internet (1 if Internet Financial Companies, 0 otherwise) and Research (1 if research position, 0 otherwise) are dummies. Robust standard errors (SE) are in parentheses, clustered at the resumes pair are in parentheses. All regressions are OLS estimations and control for city, city level, company type, ownership type of company, listed dummy, application position type, research dummy, and requirements of application position. ***p<0.01; **p<0.05; *p<0.1.

Table A6: Look and Callback: Probit Estimation

	Whole	Male	Female
	(1)	(2)	(3)
Look	0.011*** (0.002)	0.093*** (0.000)	-0.067*** (0.002)
Male	-0.036*** (0.000)		
Look_Male	-0.000*** (0.000)		
Education	0.034*** (0.000)	0.037*** (0.000)	0.032*** (0.001)
Look_Bach_Middle	0.046*** (0.002)	-0.025*** (0.001)	0.123*** (0.006)
Look_Bach_High	0.031*** (0.002)	-0.021*** (0.000)	0.091*** (0.003)
Look_Master_High	0.014*** (0.002)	-0.078*** (0.000)	0.115*** (0.004)
BigCity	-0.286*** (0.011)	-0.282*** (0.010)	-0.205*** (0.008)
Look_BigCity	0.016*** (0.000)	0.007*** (0.000)	0.023*** (0.001)
Listed	0.000 (0.002)	0.015*** (0.005)	-0.014*** (0.000)
Look_Listed	0.012*** (0.000)	0.004*** (0.001)	0.021*** (0.001)
Look_Private	0.005*** (0.000)	-0.009*** (0.000)	0.012*** (0.002)
Look_Internet	-0.004*** (0.000)	0.005*** (0.000)	-0.014*** (0.000)
Research	-0.234** (0.093)	0.033*** (0.011)	0.624*** (0.142)
Look_Research	0.011*** (0.000)	0.017*** (0.000)	0.004*** (0.001)
Observations	9,880	4,902	4,974

Dependent Variable (Callback: 1 if receiving interview call, 0 otherwise) and Look (1 if attractive, 0 otherwise) are dummies. Bach_Low, Bach_Middle, Bach_High, and Master_High equals 1 if one is the graduate respectively as a low-quality bachelor, middle-quality bachelor, high-quality bachelor, and high-quality master, 0 otherwise. BigCity (1 if first-tier cities, 0 otherwise), Listed (1 if listed, 0 otherwise), Private (1 if private companies, 0 otherwise), Internet (1 if Internet Financial Companies, 0 otherwise) and Research (1 if research position, 0 otherwise) are dummies. Marginal effects computed as the discrete change in the probability associated with the variables, evaluating other variables at their means. Standard errors are computed based on clustering at the resumes pair. Other controls include city, city level, company type, ownership type of company, listed dummy, application position type, research dummy. All controls are interacted with “Look” so main effect of “Look” is not meaningful. ***p<0.01; **p<0.05; *p<0.1.

Table B1: Beauty Score and Callback by Gender: Fixed Effect Estimation

	Whole				Male (M)		Female (F)		Diff (M vs. F)
	(1)		(2)		(3)		(4)		(5)
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	p-value
Beauty_Score	0.023***	(0.001)	0.024***	(0.002)	0.022***	(0.002)	0.024***	(0.002)	0.228
Beauty_Score_Male			-0.002	(0.003)					

Dependent Variable (Callback: 1 if receiving interview call, 0 otherwise) and Male (1 if male, 0 otherwise) are dummies. Diff (M vs. F) reports the test result of hypothesis: whether the coefficient of males subsample equals that of females subsample. Standard errors (SE) in parentheses are robust to heteroscedasticity. All regressions are fixed effect estimations and control for city, city level, company type, ownership type of company, listed dummy, application position type, research dummy, and requirements of application position. ***p<0.01; **p<0.05; *p<0.1.

Table B2: Beauty Score and Callback by Education: Fixed Effect Estimation

	Whole		Male (M)		Female (F)		Diff (M vs. F)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Coeff.	SE	Coeff.	SE	Coeff.	SE	P-value
<i>Panel A: Whole</i>							
Beauty_Score	0.031***	(0.005)	0.050***	(0.008)	0.010*	(0.006)	0.000
Beauty_Score_Education	-0.003*	(0.002)	-0.010***	(0.002)	0.005**	(0.002)	0.000
<i>Panel B: Low-Quality Bachelor</i>							
Beauty_Score	0.049***	(0.008)	0.078***	(0.014)	0.018**	(0.007)	0.000
<i>Panel C: Middle-Quality Bachelor</i>							
Beauty_Score	0.017***	(0.002)	0.018***	(0.003)	0.017***	(0.003)	0.858
<i>Panel D: High-Quality Bachelor</i>							
Beauty_Score	0.026***	(0.002)	0.024***	(0.003)	0.027***	(0.003)	0.421
<i>Panel E: High-Quality Master</i>							
Beauty_Score	0.020***	(0.002)	0.013***	(0.003)	0.028***	(0.004)	0.000
Diff (B vs. C)	0.000		0.000		0.866		
Diff (B vs. D)	0.000		0.000		0.108		
Diff (B vs. E)	0.000		0.000		0.087		
Diff (C vs. D)	0.000		0.037		0.003		
Diff (C vs. E)	0.237		0.102		0.003		
Diff (D vs. E)	0.014		0.000		0.821		

Dependent Variable (Callback: 1 if receiving interview call, 0 otherwise) is dummy. Education is an ordinal variable (1: low-quality bachelor; 2: middle-quality bachelor; 3: high-quality bachelor; 4: high-quality master). Diff (M vs. F) reports the test result of hypothesis: whether the coefficient of males subsample equals that of females subsample. Diff (X vs. Y) reports the test result (p-value) of hypothesis: whether the coefficient of Panel X equals that of Panel Y. Standard errors (SE) in parentheses are robust to heteroscedasticity. All regressions are fixed effect estimations and control for city, city level, company type, ownership type of company, listed dummy, application position type, research dummy, and requirements of application position. ***p<0.01; **p<0.05; *p<0.1.

Table B3: Beauty Score and Callback by Employers Attributes: Fixed Effect Estimation

	Whole		Male (M)		Female (F)		Diff (M vs. F)
	(1)		(2)		(3)		(4)
	Coeff.	SE	Coeff.	SE	Coeff.	SE	p-value
<i>Panel A1: City Level</i>							
Beauty_Score	0.020***	(0.002)	0.022***	(0.003)	0.019***	(0.003)	0.279
Beauty_Score_BigCity	0.004	(0.003)	0.000	(0.004)	0.009**	(0.004)	0.030
<i>Panel A2: First-Tier Cities (BigCity=1)</i>							
Beauty_Score	0.025***	(0.002)	0.022***	(0.002)	0.027***	(0.003)	0.035
<i>Panel A3: Second-Tier Cities (BigCity=0)</i>							
Beauty_Score	0.020***	(0.002)	0.022***	(0.003)	0.019***	(0.003)	0.279
Diff (A2 vs. A3)	0.031		0.955		0.002		
<i>Panel B1: Listed Status</i>							
Beauty_Score	0.022***	(0.001)	0.022***	(0.002)	0.023***	(0.002)	0.476
Beauty_Score_Listed	0.005	(0.004)	0.002	(0.006)	0.009	(0.006)	0.288
<i>Panel B2: Listed Companies (Listed=1)</i>							
Beauty_Score	0.028***	(0.004)	0.024***	(0.005)	0.032***	(0.006)	0.167
<i>Panel B3: Non-Listed Companies (Listed=0)</i>							
Beauty_Score	0.022***	(0.001)	0.022***	(0.002)	0.023***	(0.002)	0.476
Diff (B2 vs. B3)	0.079		0.588		0.059		
<i>Panel C1: Company Ownership</i>							
Beauty_Score	0.023***	(0.007)	0.027***	(0.010)	0.020**	(0.009)	0.433
Beauty_Score_Private	-0.000	(0.007)	-0.005	(0.010)	0.005	(0.009)	0.291
<i>Panel C2: Private Companies (Private=1)</i>							
Beauty_Score	0.023***	(0.001)	0.022***	(0.002)	0.024***	(0.002)	0.162
<i>Panel C3: Non-Private Companies (Private=0)</i>							
Beauty_Score	0.023***	(0.007)	0.027***	(0.010)	0.020**	(0.009)	0.434
Diff (C2 vs. C3)	0.629		0.457		0.452		
<i>Panel D1: Company Industry</i>							
Beauty_Score	0.023***	(0.001)	0.022***	(0.002)	0.025***	(0.002)	0.131
Beauty_Score_Internet	-0.001	(0.004)	0.001	(0.005)	-0.004	(0.005)	0.282
<i>Panel D2: Internet Financial Companies (Internet=1)</i>							
Beauty_Score	0.022***	(0.003)	0.023***	(0.005)	0.021***	(0.005)	0.604
<i>Panel D3: Other Companies (Internet=0)</i>							
Beauty_Score	0.023***	(0.001)	0.022***	(0.002)	0.025***	(0.002)	0.131
Diff (D2 vs. D3)	0.629		0.699		0.255		

Dependent Variable (Callback: 1 if receiving interview call, 0 otherwise) is dummy. Diff (M vs. F) reports the test result of hypothesis: whether the coefficient of males subsample equals that of females subsample. Diff (X vs. Y) reports the test result (p-value) of hypothesis: whether the coefficient of Panel X equals that of Panel Y. Standard errors (SE) in parentheses are robust to heteroscedasticity. All regressions are fixed effect estimations and control for city, city level, company type, ownership type of company, listed dummy, application position type, research dummy, and requirements of application position. ***p<0.01; **p<0.05; *p<0.1.

Table B4: Beauty Score and Callback by Job Features: Fixed Effect Estimation

	Whole		Male (M)		Female (F)		Diff (M vs. F)
	(1)		(2)		(3)		(4)
	Coeff.	SE	Coeff.	SE	Coeff.	SE	p-value
<i>Panel A1: Research vs. Sales Vacancies</i>							
Beauty_Score	0.021***	(0.002)	0.018***	(0.002)	0.025***	(0.003)	0.007
Beauty_Score_Research	0.004	(0.003)	0.008**	(0.004)	-0.001	(0.004)	0.014
<i>Panel A2: Research (Research=1)</i>							
Beauty_Score	0.025***	(0.002)	0.026***	(0.003)	0.024***	(0.003)	0.448
<i>Panel A3: Sale (Research=0)</i>							
Beauty_Score	0.021***	(0.002)	0.018***	(0.002)	0.025***	(0.003)	0.007
Diff (A2 vs. A3)	0.059		0.002		0.646		
<i>Panel B1: Education Requirement and Payment</i>							
Beauty_Score	0.021***	(0.002)	0.017***	(0.002)	0.025***	(0.003)	0.005
Beauty_Score_High-Payment	0.004	(0.003)	0.009**	(0.004)	-0.002	(0.004)	0.008
<i>Panel B2: High Education and High Payment (High-Payment=1)</i>							
Beauty_Score	0.025***	(0.002)	0.026***	(0.003)	0.024***	(0.003)	0.371
<i>Panel B3: Low Education and Low Payment (High-Payment=0)</i>							
Beauty_Score	0.021***	(0.002)	0.017***	(0.002)	0.025***	(0.003)	0.005
Diff (B2 vs. B3)	0.056		0.001		0.564		

Dependent Variable (Callback: 1 if receiving interview call, 0 otherwise) is dummy. Diff (M vs. F) reports the test result of hypothesis: whether the coefficient of males subsample equals that of females subsample. Diff (X vs. Y) reports the test result (p-value) of hypothesis: whether the coefficient of Panel X equals that of Panel Y. Standard errors (SE) in parentheses are robust to heteroscedasticity. All regressions are fixed effect estimations and control for city, city level, company type, ownership type of company, listed dummy, application position type, research dummy, and requirements of application position. ***p<0.01; **p<0.05; *p<0.1.

Table B5: Beauty Score and Callback: Fixed Effect Estimation Including All Interaction Terms

	Whole		Male (M)		Female (F)		Diff (M vs. F)
	(1)		(2)		(3)		(4)
	Coeff.	SE	Coeff.	SE	Coeff.	SE	p-value
Beauty_Score	0.044***	(0.011)	0.078***	(0.017)	0.004	(0.013)	0.000
Beauty_Score_Male	-0.002	(0.003)					
Beauty_Score_Bach_Middle	-0.031***	(0.008)	-0.060***	(0.014)	-0.001	(0.008)	0.000
Beauty_Score_Bach_High	-0.023***	(0.009)	-0.053***	(0.014)	0.010	(0.008)	0.000
Beauty_Score_Master_High	-0.028***	(0.008)	-0.064***	(0.014)	0.010	(0.008)	0.000
Beauty_Score_BigCity	0.004	(0.003)	-0.000	(0.004)	0.009**	(0.004)	0.019
Beauty_Score_Listed	0.005	(0.004)	0.002	(0.006)	0.009	(0.007)	0.308
Beauty_Score_Private	0.002	(0.007)	-0.003	(0.010)	0.007	(0.009)	0.308
Beauty_Score_Internet	0.000	(0.004)	0.004	(0.005)	-0.003	(0.005)	0.194
Beauty_Score_Research	0.001	(0.003)	0.002	(0.004)	0.001	(0.004)	0.771
Observations	9,892		4,910		4,982		
R ²	0.062		0.079		0.062		

Dependent Variable (Callback: 1 if receiving interview call, 0 otherwise) and Male (1 if male, 0 otherwise) are dummies. Bach_Low, Bach_Middle, Bach_High, and Master_High equals 1 if one is the graduate respectively as a low-quality bachelor, middle-quality bachelor, high-quality bachelor, and high-quality master, 0 otherwise. BigCity (1 if first-tier cities, 0 otherwise), Listed (1 if listed, 0 otherwise), Private (1 if private companies, 0 otherwise), Internet (1 if Internet Financial Companies, 0 otherwise) and Research (1 if research position, 0 otherwise) are dummies. Standard errors (SE) in parentheses are robust to heteroscedasticity. All regressions are fixed effect estimations and control for city, city level, company type, ownership type of company, listed dummy, application position type, research dummy, and requirements of application position. ***p<0.01; **p<0.05; *p<0.1.

Table C1: Beauty Score and Callback by Gender: OLS Estimation

	Whole				Male (M)		Female (F)	
	(1)		(2)		(3)		(4)	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Beauty_Score	0.023***	(0.000)	0.024***	(0.000)	0.022***	(0.000)	0.024***	(0.000)
Beauty_Score_Male			-0.002***	(0.000)				

Dependent Variable (Callback: 1 if receiving interview call, 0 otherwise) and Male (1 if male, 0 otherwise) are dummies. Diff (M vs. F) reports the test result of hypothesis: whether the coefficient of males subsample equals that of females subsample. Robust standard errors (SE) are in parentheses, clustered at the resumes pair are in parentheses. All regressions are OLS estimations and control for city, city level, company type, ownership type of company, listed dummy, application position type, research dummy, and requirements of application position. ***p<0.01; **p<0.05; *p<0.1.

Table C2: Beauty Score and Callback by Education: OLS Estimation

	Whole		Male (M)		Female (F)	
	(1)		(2)		(3)	
	Coeff.	SE	Coeff.	SE	Coeff.	SE
<i>Panel A: Whole</i>						
Beauty_Score	0.032**	(0.002)	0.050***	(0.000)	0.010***	(0.000)
Beauty_Score_Education	-0.003	(0.001)	-0.010***	(0.000)	0.005***	(0.000)
<i>Panel B: Low-Quality Bachelor (Education=1)</i>						
Beauty_Score	0.049***	(0.000)	0.078***	(0.000)	0.018***	(0.000)
<i>Panel C: Middle-Quality Bachelor (Education=2)</i>						
Beauty_Score	0.017***	(0.000)	0.018***	(0.000)	0.017***	(0.000)
<i>Panel D: High-Quality Bachelor (Education=3)</i>						
Beauty_Score	0.026***	(0.000)	0.024***	(0.000)	0.027***	(0.000)
<i>Panel E: High-Quality Master (Education=4)</i>						
Beauty_Score	0.020***	(0.000)	0.013***	(0.000)	0.028***	(0.000)

Dependent Variable (Callback: 1 if receiving interview call, 0 otherwise) is dummy. Education is an ordinal variable (1: low-quality bachelor; 2: middle-quality bachelor; 3: high-quality bachelor; 4: high-quality master). Robust standard errors (SE) are in parentheses, clustered at the resumes pair are in parentheses. All regressions are OLS estimations and control for city, city level, company type, ownership type of company, listed dummy, application position type, research dummy, and requirements of application position. ***p<0.01; **p<0.05; *p<0.1.

Table C3: Beauty Score and Callback by Employers Attributes: OLS Estimation

	Whole		Male (M)		Female (F)	
	(1)		(2)		(3)	
	Coeff.	SE	Coeff.	SE	Coeff.	SE
<i>Panel A1: City Level</i>						
Beauty_Score	0.021**	(0.000)	0.022***	(0.000)	0.019***	(0.000)
Beauty_Score_BigCity	0.004	(0.001)	0.000***	(0.000)	0.009***	(0.000)
<i>Panel A2: First-Tier Cities (BigCity=1)</i>						
Beauty_Score	0.025***	(0.000)	0.022***	(0.000)	0.027***	(0.000)
<i>Panel A3: Second-Tier Cities (BigCity=0)</i>						
Beauty_Score	0.020***	(0.000)	0.022***	(0.000)	0.019***	(0.000)
<i>Panel B1: Listed Status</i>						
Beauty_Score	0.022***	(0.000)	0.022***	(0.000)	0.023***	(0.000)
Beauty_Score_Listed	0.006**	(0.000)	0.002***	(0.000)	0.009***	(0.000)
<i>Panel B2: Listed Companies (Listed=1)</i>						
Beauty_Score	0.028***	(0.000)	0.024***	(0.000)	0.032***	(0.000)
<i>Panel B3: Non-Listed Companies (Listed=0)</i>						
Beauty_Score	0.022***	(0.000)	0.022***	(0.000)	0.023***	(0.000)
<i>Panel C1: Company Ownership</i>						
Beauty_Score	0.025**	(0.001)	0.027***	(0.000)	0.020***	(0.000)
Beauty_Score_Private	-0.002	(0.001)	-0.005***	(0.000)	0.005***	(0.000)
<i>Panel C2: Private Companies (Private=1)</i>						
Beauty_Score	0.023***	(0.000)	0.022***	(0.000)	0.024***	(0.000)
<i>Panel C3: Non-Private Companies (Private=0)</i>						
Beauty_Score	0.023***	(0.000)	0.027***	(0.000)	0.020***	(0.000)
<i>Panel D1: Company Industry</i>						
Beauty_Score	0.024***	(0.000)	0.022***	(0.000)	0.025***	(0.000)
Beauty_Score_Internet	-0.003***	(0.000)	0.001***	(0.000)	-0.004***	(0.000)
<i>Panel D2: Internet Financial Companies (Internet=1)</i>						
Beauty_Score	0.022***	(0.000)	0.023***	(0.000)	0.021***	(0.000)
<i>Panel D3: Other Companies (Internet=0)</i>						
Beauty_Score	0.023***	(0.000)	0.022***	(0.000)	0.025***	(0.000)

Dependent Variable (Callback: 1 if receiving interview call, 0 otherwise) is dummy. Robust standard errors (SE) are in parentheses, clustered at the resumes pair are in parentheses. All regressions are OLS estimations and control for city, city level, company type, ownership type of company, listed dummy, application position type, research dummy, and requirements of application position. ***p<0.01; **p<0.05; *p<0.1.

Table C4: Beauty Score and Callback by Job Features: OLS Estimation

	Whole		Male (M)		Female (F)	
	(1)		(2)		(3)	
	Coeff.	SE	Coeff.	SE	Coeff.	SE
<i>Panel A1: Research vs. Sales Vacancies</i>						
Beauty_Score	0.021***	(0.000)	0.018***	(0.000)	0.025***	(0.000)
Beauty_Score_Research	0.003*	(0.000)	0.008***	(0.000)	-0.001***	(0.000)
<i>Panel A2: Research (Research=1)</i>						
Beauty_Score	0.025***	(0.000)	0.026***	(0.000)	0.024***	(0.000)
<i>Panel A3: Sale (Research=0)</i>						
Beauty_Score	0.021***	(0.000)	0.018***	(0.000)	0.025***	(0.000)
<i>Panel B1: Education Requirement and Payment</i>						
Beauty_Score	0.021***	(0.000)	0.017***	(0.000)	0.025***	(0.000)
Beauty_Score_High-Payment	0.003*	(0.000)	0.009***	(0.000)	-0.002***	(0.000)
<i>Panel B2: High Education and High Payment (High-Payment=1)</i>						
Beauty_Score	0.025***	(0.000)	0.026***	(0.000)	0.024***	(0.000)
<i>Panel B3: Low Education and Low Payment (High-Payment=0)</i>						
Beauty_Score	0.021***	(0.000)	0.017***	(0.000)	0.025***	(0.000)

Dependent Variable (Callback: 1 if receiving interview call, 0 otherwise) is dummy. Robust standard errors (SE) are in parentheses, clustered at the resumes pair are in parentheses. All regressions are OLS estimations and control for city, city level, company type, ownership type of company, listed dummy, application position type, research dummy, and requirements of application position. ***p<0.01; **p<0.05; *p<0.1.

Table C5: Beauty Score and Callback: OLS Estimation Including All Interaction Terms

	Whole		Male (M)		Female (F)	
	(1)		(2)		(3)	
	Coeff.	SE	Coeff.	SE	Coeff.	SE
Beauty_Score	0.015	(0.009)	0.031	(0.010)	-0.011	(0.003)
Beauty_Score_Male	-0.002**	(0.000)				
Beauty_Score_Bach_Middle	0.011	(0.010)	-0.000	(0.012)	0.024	(0.005)
Beauty_Score_Bach_High	0.005	(0.008)	-0.007	(0.010)	0.020*	(0.002)
Beauty_Score_Master_High	0.001	(0.009)	-0.021	(0.009)	0.028*	(0.003)
Beauty_Score_BigCity	0.004	(0.001)	0.001	(0.000)	0.008**	(0.000)
Beauty_Score_Listed	0.006**	(0.000)	0.002**	(0.000)	0.009***	(0.000)
Beauty_Score_Private	0.000	(0.001)	-0.005**	(0.000)	0.007***	(0.000)
Beauty_Score_Internet	-0.002*	(0.000)	0.002*	(0.000)	-0.004**	(0.000)
Beauty_Score_Research	0.003*	(0.000)	0.007*	(0.001)	0.001**	(0.000)
Observations	9,892		4,910		4,982	
R ²	0.062		0.079		0.062	

Dependent Variable (Callback: 1 if receiving interview call, 0 otherwise) and Male (1 if male, 0 otherwise) are dummies. Bach_Low, Bach_Middle, Bach_High, and Master_High equals 1 if one is the graduate respectively as a low-quality bachelor, middle-quality bachelor, high-quality bachelor, and high-quality master, 0 otherwise. BigCity (1 if first-tier cities, 0 otherwise), Listed (1 if listed, 0 otherwise), Private (1 if private companies, 0 otherwise), Internet (1 if Internet Financial Companies, 0 otherwise) and Research (1 if research position, 0 otherwise) are dummies. Robust standard errors (SE) are in parentheses, clustered at the resumes pair are in parentheses. All regressions are OLS estimations and control for city, city level, company type, ownership type of company, listed dummy, application position type, research dummy, and requirements of application position. ***p<0.01; **p<0.05; *p<0.1.