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Beautiful people earn more. Surprisingly, this premium is larger for men than for women and is independent of the degree of customer contact. Overlooked is the possibility that beauty can influence college admissions. We explore this academic contributor to the labor market beauty earnings premium by sampling 1,800 social media profiles of students from universities ranked from 1 to 200 in China and the US. Chinese universities use only standardized test scores for admissions. In contrast, US universities use also grades and extracurricular activities, which are not necessarily beauty-blind. Consistent with beauty-blind admissions, alumni's beauty is uncorrelated with the rank of college attended in China. In the US, White men from higher ranked colleges are better-looking. As expected, the correlation is insignificant for White men who attended tech colleges and is highest for those who attended private colleges. We also find that White women and minorities of either gender are not better-looking at higher ranked colleges. Our evidence indicates a college admissions contribution to the labor market beauty premium for US White men, but not for students in China of either gender, White women, or minorities of either gender in the US, or for White men who attended technology colleges. We discuss the college admissions preference for athletes as a potential channel for the positive correlation we find between college and beauty rank for White men.

Keywords: beauty premium, labor market discrimination, college admissions, college athletics

JEL Codes: J71, I24, Z22

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1 Introduction

Beautiful people earn more. Such is the conclusion of a burgeoning literature initiated by Biddle and Hamermesh (1994). Surprisingly, beauty seems to matter more for men than for women, and in most jobs, instead of being limited to those with extensive dealings with customers who might indulge a taste for beauty. (See A-Table 1 in the Appendix for a summary of the beauty premium for men and women across studies.) To explain these unexpected findings, several authors have proposed employer discrimination through the channel of human resource (HR) managers as a potential cause. However, overlooked is the possibility that part of the labor market beauty premium originates prior to the labor market, specifically in the college admissions process, within which the discretion of teachers, guidance counselors, and admissions officers to discriminate, are comparable to that of HR managers. In fact, colleges seem to do precisely that when seeking talent in "leadership, performing arts, or athletics", all factors which can be influenced by popularity, and hence, potentially by beauty among high school students.[1] In the case of the election of high school students to leadership positions, beauty may the crucial factor considering that the voting public (Berggren, Jordahl, and Poutvaara 2010) and even Ph.D. economists (Hamermesh 2006) exhibit a bias for beauty in the election of their leaders.

We test for this potential college admissions contribution to the labor market beauty premium by sampling 1,800 online social media profiles across a wide range of universities (ranked 1−200) in China and in the US. Given that US universities use extracurricular activities and grades in the decision to admit students (Green, Jaschik, and Lederman 2011), we hypothesize that the beauty rank of alumni may increase the rank of the university they attended in the US. In contrast, Chinese universities use standardized test scores almost exclusively to admit students (Bai and Chi 2014; Li et al. 2012; Yang 2014). [2] Despite the shortcomings of such an admissions system in terms of the stress it imposes on students (Cai et al. 2019), it is beauty-blind. Moreover, in light of a recent

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[1] According to a recent New York Times article (Cain 2017), 'Harvard's application informs students that its mission is "to educate our students to be citizens and citizen-leaders for society." Yale's website advises applicants that it seeks "the leaders of their generation". On Princeton's site, "leadership activities" are first among equals on a list of characteristics for would-be students to showcase. Even Wesleyan, known for its artistic culture, was found by one study to evaluate applicants based on leadership potential…Whatever the colleges' intentions, the pressure to lead now defines and constricts our children's adolescence….It seemed no activity or accomplishment meant squat unless it was somehow connected to leadership.'
https://www.nytimes.com/2017/03/24/opinion/sunday/not-leadership-material-good-the-world-needs-followers.html?_r=1

[2] A number of top-tier universities in China admit some outstanding students, e.g., winners of international mathematics competitions through special channels that involve the university's own admissions exams, followed by oral exam type interviews. However, details on the policies for specific universities are not publicly available.

large sample study of twins which finds no relationship between facial attractiveness and intelligence (Mitchem et al. 2015), we expect no association between the beauty rank of alumni and the rank of the university they attended in China, because of factors correlated with intelligence, which we expect to increase with school rank.

Our hypothesis for China is confirmed: the facial beauty of Chinese students of either gender is uncorrelated with the rank of the college they attended. Our hypothesis for the US is confirmed only for White men (74% of our male sample). Only their facial beauty increases with the rank of college attended.

We test further the hypothesis that reliance on standardized tests diminishes the association between the beauty rank of alumni and the rank of the college attended that we find for White men by checking for variation in the magnitude of the correlation across different types of colleges. We separate our sample of White men according to whether they attended private, public, or technology colleges. Compared to public colleges, private colleges can rely less on standardized tests and more on discretionary criteria than public colleges, because they are less regulated. As expected, the association between facial beauty and the rank of the college attended is stronger for private colleges. On the other hand, technology colleges should attach more weight to technical ability as indicated by standardized test scores than non-technology colleges.[3] Accordingly, we find that the association between beauty and the rank of the college attended is insignificant for alumni of technology colleges. Thus, reliance on standardized tests appears to suppress the correlation between the beauty of White men and the rank of their alma mater, while discretion in admissions criteria increases it.

Our finding that the beauty of both genders in China, White women and non-White minorities of both genders in the US, and White men in tech colleges, is not associated with the rank of their college supports prior evidence that beauty is uncorrelated with intelligence. Our contribution to this literature on the association between intelligence and beauty is to provide further evidence against an association between beauty and general academic ability, as captured through the variation in the rank of colleges. For our sample of US White women and non-White minorities of

[3] A former director of admissions at Dartmouth, an elite private college, revealed that it was very difficult to choose from among the many academically well-qualified candidates of the two thousand applications she read per year (Sabky 2017). In her view, personal essays by the candidate and letters of recommendation from illustriousness mentors are generally uninformative. Rather, she must resort to idiosyncratic signals such as "inappropriate email addresses", behavior on a campus visit, or an unusual recommender—in the case of the article--the janitor of the student's high school. Additionally, she sometimes give those signals greater priority than standardized test scores in her admissions decision. See: https://www.nytimes.com/2017/04/04/opinion/check-this-box-if-youre-a-good-person.html?mtrref=query.nytimes.com&assetType=opinion

both genders, we also provide evidence that beauty is not associated with non-academic criteria, e.g., leadership qualities for both genders and athletic ability for women, that US colleges also use for admitting students.

We check for the simple association between the rank of the college attended and post-graduation wages to get a sense of the potential economic importance of the college admissions contribution to the labor market beauty premium for White men. For this sample of subjects, a one percentage point increase in beauty rank corresponds to a half college rank increase in the rank of the college attended. This correspondence translates in to a roughly three percent decrease in salary 10 years after graduation for a 10 percent decrease in beauty rank.

The association between beauty and earnings for White men that we find is of a similar magnitude to that previously found for the labor market beauty premium, which ranges from 5-20 percent for the coarser measure of below, at, or above average looks (A-Table 1). In principle, it is possible for the variation in the beauty of White men to be of comparable magnitude because, while these previous studies of the labor market beauty premium do control for years of education, they do not control for the rank of college among those who graduated from college.

We contribute to the literature on the labor market beauty premium by providing evidence which suggests a college admission contribution to the labor market beauty earnings premium for men in the US, who are mostly White.[4] This college admissions contribution may help explain the surprisingly greater labor market beauty premium for men in the US, and why it does not vary across jobs with significant and insignificant exposure to customers. Our evidence suggests that the labor market beauty premium for men and women in China (Deng, Li, and Zhou 2019; Gu and Ji 2019; Hamermesh, Meng, and Zhang 2002; Maurer-Fazio and Lei 2015) and for women and non-Whites of both genders in the US may arise after college. Our results also suggest the potential importance of controlling not only for the years of education in future studies of the labor market beauty premium, but also for the rank of the college attended, particularly for men in the US.

Section 2 reviews a few of the many studies on the beauty premium in the labor market as well as the small number of studies in the educational context. Section 3 elaborates on our methods for the collection of photos and rating of photos from social media profiles. Section 4 explains our two-stage regression strategy, where we use the residuals from the first-stage regression of beauty ratings on such factors as age and race as the basis for our second-stage regression of college rank on beauty rank. Section 5 summarizes our results, discusses potential confounders, and outlines the literature on the favoritism shown towards athletes in college admissions in the US, which may help explain our finding that only White men's beauty rank increases with the rank of the college they attended.

2 Review of labor market studies on the labor market beauty premium

Several empirical studies have demonstrated a robust labor market beauty premium for workers around the world and in various sectors beginning with the seminal work of Biddle and Hamermesh (1994). The theories of labor market discrimination by beauty parallel those of other forms of labor market discrimination, e.g., by race. These fall under two broad categories: taste-based discrimination (Becker 1971), where the discriminated characteristic, in this case, beauty, enters directly into the utility function, and productivity-based or statistical discrimination (Arrow 1973), where the observable characteristic, also beauty, is correlated with the characteristic that that influences productivity. As an example of the taste-based discrimination, customers, e.g., purchasers of fashion magazines, can derive utility directly from better-looking workers. As an example of the latter statistical discrimination, employers may discriminate by hiring good-looking people because beauty signals pleasant manners and good social skills, which are not as immediately observable as beauty. Employers may value such skills because they either increase customer satisfaction or the productivity of other workers. Alternatively, consumers can use beauty to infer other characteristics, e.g., competence in doctors, because of a possible statistical relationship between beauty and cognitive and non-cognitive skills.

Since the inception of the literature, a notable and surprisingly larger beauty premium/plainness penalty has existed for men than for women (Borland and Leigh 2014; Doorley and Sierminska 2015; Hamermesh and Biddle 1994; Harper 2000; Mocan and Tekin 2010). Moreover, the importance of looks as revealed through employer surveys on the amount of interaction with customers show little explanatory power for the cross-sectional beauty premium (Doorley and Sierminska 2015; Hamermesh and Biddle 1994). See A-Table 1 in the Appendix. While the constancy of the beauty premium across jobs can be explained by employer discrimination, that would not seem to predict a larger premium for men than for women.

These unexpected findings highlight other potential problems in identifying the source of the labor market beauty premium. Other factors can increase a person's ability to make themselves more beautiful, which, in turn, increases their wages. For example, intelligence, which is generally associated with productivity in most jobs, can potentially increase the skill with which flattering clothes (which has been shown to add to the income of women (Hamermesh, Meng, and Zhang 2002)) are chosen. Alternatively, intelligence can free up more time from other tasks with which to choose these clothes. Intelligence can also increase confidence, which may enhance the impression a person makes, e.g., if confidence in one's ability makes one smile more easily, and if smiling enhances attractiveness. Accordingly, more intelligent workers can appear more attractive, thereby earning higher wages, although they are not necessarily more physically attractive. Customers may not derive utility from the exceptional intelligence of those workers. Instead, these customers can derive utility from the friendliness of more confident workers, e.g., in a restaurant host/hostess.

Aside from intelligence, a myriad of other factors related to productivity including health and family income can conceivably contribute to both the beauty of workers and their wages. Thus, important confounders for both taste-based and statistical discrimination for the labor market beauty premium exist. In addition to the identification problems, the gender difference in significance can also be due to out-selection by attractive/unattractive women from the labor market, which again, is difficult to control for in empirical studies of the labor market.

To minimize the effects of statistical discrimination and out-selection, several researchers in the beauty premium literature used CV correspondence studies of employers. These correspondence studies are widely used to explore ethnic and gender discrimination (Bertrand and Mullainathan 2004). Such studies with employers can decrease the effects of these confounders through random assignment of beauty to the characteristics associated with beauty, e.g., intelligence, which is signaled by education in the CVs. Confirming prior empirical findings of a beauty premium, a CV correspondence study in Argentina finds that distorted photos of real people designed to make them ugly were much less likely to obtain a callback López et al. (2013). With the exception of the pronounced premium for better-looking women in office support, receptionist, and customer service jobs, the authors ascertained roughly the same positive premium for both genders across jobs, irrespective of the degree of customer contact.

A significant premium across all four occupations was observed in China, including areas such as software engineering, which has minimal customer contact (Maurer-Fazio and Lei 2015). A correspondence study in Israel using resumes with randomized photos of applicants with varying beauty shows that only better-looking men were more likely to receive a callback to a job application, whereas women suffered a beauty penalty in terms of callback rates, and even in jobs which, as the authors point out, beauty plays no obvious role: accounts management, budgeting, industrial engineering, and computer programming (2015).

However, despite the many positive findings on labor market discrimination by beauty, the existing literature has largely ignored the possibility that the beauty premium may begin before entry into the labor market.[5] The source of the beauty premium is important both to better understand labor market discrimination and also to better target antidiscrimination regulations based on personal appearance. Such legislation has already been enacted in some states and proposed elsewhere (Hamermesh 2011; Hamermesh and Biddle 1994).

The advantage of our study with respect to identification problems in the empirical and CV correspondence study literature is that we look only at the relation between beauty (as rated by impartial observers) and general labor market productivity traits, as revealed by college rankings. Our raters are neither employers nor customers, either of whom might have a taste for beauty within particular industries (e.g., for very thin women in the modeling industry) or be concerned with unobserved productivity-related traits correlated with beauty. Thus, neither taste-based nor statistical discrimination by customers or employers are relevant to this study. Additionally, given that the profiles rated here are from pre-labor market university students, they are also less likely to be biased by those individuals who have systematically selected out of the sample by beauty for opportunities in the marriage market.

Few studies in economics are available regarding the relation between academic performance and beauty. Grade point average is predicted by physical attractiveness for grade school students of both genders in England (Hansen 2016) and for female but not for male students upon entering high school (French et al. 2009). However, the association between attractiveness and grade point

[5] Many studies exist on the correlates of beauty in educational settings in the psychology literature. Physically attractive students receive higher grades in high school and college (French et al. 2009). Attractive individuals are consistently perceived or judged more favorably than the unattractive in a number of dimensions, including intelligence, academic potential, grades, confidence, extroversion, and various social skills (Jackson, Hunter, and Hodge 1995; Mobius and Rosenblat 2006; Ritts, Patterson, and Tubbs 1992). These studies suggest that beauty is believed to be correlated with these traits. However, they do not control for these traits in their identification of beliefs. Thus, they failed to demonstrate that beauty causes the beauty premium in the labor market.

average becomes negative for males and insignificant for females when personality and grooming are controlled for (French et al. 2009). Facial attractiveness in high school can account for the attractiveness premium up to the mid-30s (Scholz and Sicinski 2015). Within an elite women's liberal arts college, a negative correlation was found between beauty and academic productivity-related traits, as measured by SAT scores (Deryugina and Shurchkov 2015). No correlation was found between beauty and productivity-related traits among lawyers who graduated from one law school (Biddle and Hamermesh 1998) and among experimental subjects (Mobius and Rosenblat 2006). Most importantly, with respect to our hypothesis, these prior studies either of single colleges, or if not, they did not test for the effect of the subject's beauty or its correlates on the rank of the subject's alma mater. Consequently, they do not rule out that the labor market beauty premium in terms earnings was due to a potential bias in the college application process.

3 Methodology

We randomly selected 30 universities in China and the US ranked from 1 to 200. Each selected college has similar rankings in at least two commonly used ranking systems. The rankings for US colleges include the U.S. News & World Report Ranking,[6] the Academic Ranking of World Universities (ARWU),[7] whereas the Chinese University Alumni Alliance Ranking (CUAA)[8] and the Wu Shulian's Chinese University Rankings[9] are for Chinese colleges. College rankings are shown in the A-Table 2 in the Appendix.

We randomly sampled 30 profiles (15 for each gender) for each college on Facebook. In the US, 72 percent of college students have a profile on Facebook.[10] We used the social media site Renren in China, which had a reported membership of 280 million in 2013.[11] In both services, users can create profiles for free with photos, other images, list of personal interests, contact information, accounts of memorable life events, and other personal information, such as educational background and employment status. Registration on the two social media sites requires filling in: name, gender, and email address or phone number. Renren also requires a birth date and

[6] http://colleges.usnews.rankingsandreviews.com/best-colleges/rankings/national-universities/data

[7] http://www.shanghairanking.com/World-University-Rankings-2015/USA.html

[8] http://www.cuaa.net/cur/2015/index_700

[9] http://edu.qq.com/zt2013/2013wsl/

[10] http://www.pewinternet.org/2015/08/19/the-demographics-of-social-media-users/

[11] Renren is the Facebook analog for college students in China, as Facebook is blocked by the Chinese Government.

educational information (either high school or college). The educational information of a Renren account can also be "verified" by a college IP address or the college email. Such verification is indicated in the profile. We used only such verified accounts. A user is also required to upload a personal photo for the profile picture.

After registration, users can add other users as "friends" with whom they can share their profile content. Users can also join common-interest user groups which are organized by workplace, college, or other categories. Users determine who can browse their pages or receive their updates with their privacy settings. On both websites, users can make their profile "public," (anyone with a membership can see their profile) or "open to friends" (only "friends" can see their profile) or "private" (only the user themselves can view their profile). Both websites allow users to search for public profiles with specific educational backgrounds.

Search engines generally employ confidential proprietary algorithms to enhance the efficiency of searches. To avoid any unobserved influences from such algorithms on our results, we selected the profile photo based on random numbers from 1 to 200 generated prior to our searches. We refer to these numbers as the 'display rank'. Hence, if we drew a number 67, we would select the 67th profile in the search engine results and that profile photo would have a display rank of 67. We drew two sets of random numbers: the second to be used in cases where the profile indicated by the first number did not have the required information or photo quality.[12] We refer to the first number drawn as the 'original' display rank. Each selected profile was that of a student who graduated from the college as an undergraduate in 2012. The profile photo must be a clear color front-view photo without any head covering. Other people or backgrounds in the photos were cropped to highlight the face of the subject. We paid raters (5 RMB/100 pairs in China and 0.75 USD/100 pairs in the US) to evaluate all profile photos using a proprietary beauty rating program, which they could access through a standard web browser.[13]

The rating program matched each photo randomly with 10 other photos of the same gender in the same country. 4,500 photo pairs are generated for each gender in each country. We used multiple raters to rate the same photo. In the US, each photo was rated 12−37 times by US raters, with a mean of 22 times. In China, each photo was rated 12−28 times, with a mean of 20 times.

[12] These criteria are available on request.

[13] At the time of writing, the exchange rate was 1 USD for 6.5 RMB. Given the few minutes it takes to rate all 100 photos, our payment was relatively high for both Mechanical Turk and China. A high wage was set to attract sufficient numbers of raters in a short time span.

Such rating frequencies are comparable to other studies (Deryugina and Shurchkov 2015). The final rating for each photo is based on the average rating of all raters of that photo. In total, 90 Chinese raters (60 male) rated all 900 Chinese photos, and 103 US raters (49 males, 86 White) rated all 900 US photos. The Chinese raters were graduate students recruited from the Peking University HSBC School of Business through a mass email. The US raters were recruited through Amazon Mechanical Turk, a project-based employment service offered by Amazon.

We also hired an additional 27 US raters to categorize the race (White, Black, Hispanic, and Asian) and age ranges (age categories: 23−26 and 27 or older) of all US photos. Chinese students are almost always of the Han majority and within the 23−26 age range because they rarely take time off before college.[14] Each US rater was asked to categorize 100 US photos. Each US photo was categorized once each by three different US raters. The final race and age categories of the US photos were determined by the ratings of the US majority raters, i.e., two or three out of three. The results of the race and age categorization for the US sample are shown in Table 1.

Raters were asked to choose the more physically attractive within each pair. Instead of asking raters for a numerical rating within a certain range of numbers, as is standard in the field (Hamermesh and Biddle 1994), we followed the methodology in Ong, Yang, and Zhang (2020) asked raters to decide only which photo of a pair is better-looking. Such a judgment may be easier and more precise than assigning a number to indicate how good-looking someone is according to a subjective numerical scale (Negahban, Oh, and Shah 2012).

Numerical beauty ratings can cluster around specific numbers, e.g., 7 or 8 out of 10. A given subject may not be consistent in their beauty ratings across a number of photos, because of fatigue, lapses in memory, or because their subjective reference benchmark level of beauty changes as they rate photos. In contrast, binary decisions require discerning only the minimal difference in beauty between two photos in side-by-side comparison. Subjects do not need to strain their memory to maintain the consistency of the ratings for photos with similar beauty, if these photos happen to have many other intervening photos. With a binary comparison, the accuracy of a subject's memory is no longer an issue. The binary decision also avoids potential scale differences across individuals, genders, and countries (e.g., where Chinese females choose higher numbers than American male raters), which can add noise to the data.

[14] The Han race constitutes 91 percent of the population of China, See https://en.wikipedia.org/wiki/Ethnic_minorities_in_China. The share of Hans is likely even higher among university students.

To deal with these sources of noise, prior studies coarsen their 1-7 scale data into three categories: below, at, or above average beauty. However, this may sacrifice the precision we exploit to establish our hypotheses below. Lastly, our reliance on the binary choices of raters means that our beauty ranking is a relative ranking within the sample, not a potentially out of sample/absolute ranking against unobserved subjective protypes of beauty that the subject has in mind and uses as a benchmark.

The software we developed aggregates the ratings for each photo into a continuous number, $Rating_i$, between 0 percent (least attractive) and 100 percent (most attractive) using the well-established Bradley–Terry model for aggregating binary comparisons into a percentile (Bradley and Terry 1952). For each photo, $Rating_i$ represents the percent of other photos that reviewers on average found less attractive than subject i. Table 2 shows the summary statics for our sample. We find that White men (0.52) and women (0.52) have higher ratings than non-Whites (0.43, 0.45). This may be due to a within-race preference, found in prior studies (Hitsch, Hortaçsu, and Ariely 2010b), among our Amazon Mechanical Turk raters, who are likely to be mostly White.

Before we study the effect of beauty rank on college rank, we first remove the effect of other factors on the beauty ratings of subjects by regressing $Rating_i$ on the display rank of profile i and the dummy variable, $Original_i$, which takes on the value of 1 if the original display rank was used to harvest the profile or 0 if the display rank was a redrawn random number.[15] This first-stage regression specification is

$$Rating_i = \alpha + \beta_1(Display\ Rank_i) + \beta_2(Original_i) + \varepsilon \qquad \text{Eq. (1)}$$

For the US photos, we also include an age category dummy and race dummies (based on the age attributed by a separate group of raters).

For this first-stage regression, we find, consistent with Bruch and Newman's (2018) important study of online dating preferences, non-White men are less attractive than White. We find this difference to be insignificant for Black and Hispanic men, but this may be due to our small sample size. However, we do find that Asian men, for whom our sample size is slightly larger, are 16 percentage points less attractive (-0.16) than White men. Also, we find in column (2), consistent with Bruch and Newman, that women who are judged older than 27 (-0.05) or are Black (-0.18) are less attractive. However, unlike Bruch and Newman, we find that Asian women, who they find

[15] We must remove the effect of age before we regress college rank on beauty to avoid including the coefficient of the subject's age on the rank of the college attended, which is not of interest to our study.

to be most attractive, are deemed less attractive than White women in our study. This difference may be due to their sample, which included subjects with only high school or post graduate education, being more heterogenous in terms of educational attainment than our sample. The insignificant and zero coefficient for display rank in columns (1)-(3) indicate Facebook does not rank profiles by factors which are correlated with attractiveness, e.g., popularity. In contrast, the negative and significant coefficient for display rank in columns (4)-(6) indicates that profiles that were further down the page in the search engine results of Renren are slightly less attractive.

[Insert Table 3]

From each of these regressions in Table 3, which are separated by gender per country, we derive a set of residual ratings, $Residual\ Rating_i$. This separation of residuals per gender per country allows us to control for potential heterogenous effects of age, race, or even display rank on the residual of the rating per country. For easier exposition, we invert the residual rating by taking the negative value of it. We also add a constant of 0.5, which was removed from the residuals in the first-stage regression. Thus, our independent variable for the second stage regression is the beauty percentile rank (henceforth, 'beauty rank'): $Beauty\ Rank_i = -Residual\ Rating_i + 0.5$. In this form, smaller numerical values of beauty rank denote more beautiful individuals (i.e., higher beauty rank), just as smaller numerical values of college rank denote greater prestige (i.e., higher college rank). Thus, we can avoid the inconvenience for our readers of interpreting a negative sign for our main findings.

For our main results, we estimate the effect of $Beauty\ Rank_i$ on $LCollege\ Rank_i$,

$$LCollege\ Rank_i = \alpha + \beta_1(Beauty\ Rank_i) + \varepsilon \qquad \text{Eq. (2)}$$

where $LCollege\ Rank_i$ is the *log* of the rank of the college that subject i attended. We choose the *log* of the college rank because we expect that the pool of applicants available to higher ranked colleges is larger than that available to lower ranked colleges. Therefore, higher ranked colleges can afford to, and indeed, may need to be choosier by soft/discretionary criteria in filling their incoming class. Moreover, we also expect that the marginal value of an increase in rank for applicants to high ranked colleges (e.g., going from second to first) to be larger than for low ranked colleges (e.g., going from top-200 to top-199). Both effects would create increasing returns to selectivity by the correlates of beauty for higher ranked colleges which the log of the college rank would partially compensate for.[16]

4 Results

Table 4 displays the effect of the beauty rank on the *log* college rank. Columns (1)-(2) show that the coefficients for men (0.08) and for women (-0.03) in China are close to zero and not significant. Column (3) indicates that they are not significantly different from each other.

Observation I. The beauty rank of alumni of either gender in China has no economically or statistically significant association to the rank of the college attended.

Column (4) reveals that the coefficients men (0.64) in the US is significant and positive, while column (5) reveals that the coefficient for women is small (-0.02) and not significantly different from zero. Column (6) indicates that the coefficient for women is not significantly different from the men's. This lack of significance is most likely because the standard error for the coefficient of women's beauty rank is large.

Observation II. The beauty rank of male alumni but not female alumni in the US increases on the rank of the college attended.

Translating these results back to the original non-*log* college rank, in the case of US men, the constant of 3.82 implies that when the beauty rank is highest (i.e., 0), the college rank is $e^{3.82} = 47$. When the beauty rank is lowest (i.e., 100), the college rank is $e^{3.82+0.75} = 97$. The difference is 50 ranks. Hence, for a one rank increase in beauty rank, there is on average a 0.5 rank increase in the rank of the college attended.

White men and women make up the largest part (660/900 = 73%) of the sample. To check for racial differences, we separate the sample by White and non-White in Table 5. Column (1) of Table 5 reveals that the coefficient for beauty rank is not significant for non-White men and is significant for White men (0.75). Column (3) reveals that the difference between White and non-White men is insignificant. This lack of significance is most likely due to the large standard error for the non-

[16] Our results are qualitatively and quantitatively nearly identical when we do not use the log transformation. These results are available on request.

White men revealed in column (1). Columns (4) and (5) shows that the rank of the college attended by non-White and White women does not increase with their beauty rank.[17]

Observation III. The beauty rank of White male alumni but not White female or non-White alumni of either gender increases significantly with the rank of the college attended in the US.

Figure 1 displays the plot of the *log* rank of the college attended against the beauty rank of alumni for White men and women. The right panel shows that the men's beauty rank monotonically increases on the rank of the college attended, whereas the left panel shows that of women does not.

We hypothesize that the correlates of beauty might affect admissions in the US through the exercise of discretion as to the merits signaled by extracurricular activities. According to this hypothesis, we should find a greater association between the beauty and the college ranks for alumni who attended private colleges, which have greater discretion in the interpretation of such criteria because they are less regulated. To test this hypothesis, we redo the previous regressions by comparing results with and without private colleges (namely, Harvard, Columbia, Penn, Massachusetts Institute of Technology, New York University, Boston University, Stevens Institute of Technology, Illinois Institute of Technology, and New Jersey Institute of Technology) in Table 6. The coefficient for beauty rank increases from 0.32 in column (1) for public colleges to 1.74 in column (2) for private colleges, suggesting that an incremental increase in the beauty rank is associated with a greater increase in the rank of college attended among alumni of private colleges. This greater association is confirmed in column (5) with the positive coefficient for the interaction of the private dummy variable and beauty rank (1.43) for the full sample of both private and public colleges.

[17] A-Table 3 shows that the coefficients for non-White races of either gender are negative, but too imprecisely measured to be statistically significant. This lack of significance does not seem to be due to the sample sizes being smaller than that of Whites, however. For non-White men and women, we have 119 and 121 observations, respectively. Both are nearly twice as large as the number of observations that we have for White men in private colleges for column (2) of Table 6, which was still significant at the 5 percent level. However, many of the sample sizes for the coefficients for the correlation of disaggregated minorities in columns (3)-(8) are too small to draw any inference. Hence, we make an observation for the non-Whites, and merely remark that the disaggregated data is consistent with the aggregate.

This finding of a higher slope for the regression of the *log* of college rank on beauty rank, along with a lower intercept for private as compared to publics colleges, raises the possibility that private colleges can themselves be more heterogeneous than public colleges in terms of how much the correlates of beauty affect the chance of admissions of White men. A potential reason for the greater level of heterogeneity among private as compared to public colleges is, higher ranked private colleges might use their greater discretion in order to reject more otherwise similarly qualified students, while lower ranked private colleges may use their greater discretion to admit more marginal candidates.

To test the hypothesis that higher ranked private colleges are more selective than lower ranked private colleges in terms of beauty (or its correlates), we drop subjects from the top-four private colleges from our sample: Harvard, Columbia, Penn, MIT, that are ‘top-10’ in column (3), while leaving in the bottom-five private colleges in the sample. The coefficient of beauty rank decreases from 0.75 in column (2) of Table 5 to 0.23 in column (3) Table 6. If we drop subjects from the bottom-four ranked private colleges in our sample: Boston University, Stevens, IIT, and NJIT in column (4), the coefficient increases to 0.78. These results are consistent with the possibility that beauty or its correlates may have a much larger effect for admissions to the top private colleges than to the lower ranked private colleges.

Columns (6-8) exhibit results for technology colleges, which may rely less than non-technical colleges on discretion and more on standardized tests. This conjecture is confirmed by the contrast between the significant coefficient for beauty rank (0.84) in column (6) which drops subjects from technology colleges and the insignificant coefficient for beauty rank (0.26) in column (7) which contains data of subjects only from technology colleges. However, the insignificance of the technology beauty rank interaction in column (8) does not give further support.

Observation IV. The positive correlation between the beauty rank of White male alumni and the college they attended is stronger among those who attended private colleges and weaker among those who attended technology colleges.

These findings of no significant correlation between the beauty rank of alumni and the rank of their college for students of both genders in China, White women, and non-White minorities of both genders and White men in tech colleges in the US, suggests that the correlation we find for White men is due to non-academic factors used in the admissions process. We discuss some potential non-academic factors in the admissions process which might interact with the beauty of White men, in particular, in Section 5.

To get a rough sense of the potential impact of the correlates of beauty rank on salary, we perform a simple regression of the median and the expected salary (not broken down by race or gender) on the rank of the college attended in Table 7. (See A-Table 2 for the salary data.)

[Insert Table 7]

Columns (1) and (2) show the mean and median salaries in the 2011 for those who enrolled in 2001 in the US. Columns (1) and (2) reveals that for the US (starting from the highest-ranking university), an incremental decrease in college rank for a student enrolled in 2001 decreases their mean salary by approximately 374 USD and median salary by approximately 471 USD per year, respectively, in 2011. Thus, a percentage point decrease in beauty rank corresponds to a decrease of 0.3 percent in mean (50/100·(-374/72,991)) and median (50/100·(-471/78,546)) salaries 10 years later. This association, and therefore, potential effect of beauty, is sizeable when compared to prior studies which use the coarser ratings: below, at, or above average looks. Our findings suggest that a 33 percent increase in beauty rating would result in a 10 percent increase in salary 10 years after graduation.

5 Discussion and Conclusion

We find the facial beauty rank of alumni of either gender has no economically or statistically significant effect on the rank of the college they attended in China (Observation I). The beauty rank of male alumni but not female alumni in the US increases on the rank of the college attended (Observation II). When the US sample is broken down by race, we find that the beauty rank of only White male alumni is significantly associated with the rank of the college attended. The beauty rank of White female alumni and non-White alumni of either gender are not significantly associated with college rank (Observation III). The association of the beauty rank for White male alumni is strongest for higher ranked private colleges, which are presumably less regulated. In contrast, the beauty rank of White male alumni from technology colleges has no significant association with the rank of the college attended (Observation IV). The association between the beauty rank and school attended for White male alumni implies that, an increase in beauty rank of 33 percent is associated with a 10 percent higher salary 10 years after graduation. This is within

5-20 percent range for men (who are mostly White) with above average looks (within above, at, or below average looks framework) found in previous studies (A-Table 1).

Importantly for interpreting these results, our finding in China suggests that beauty is not statistically significantly associated with college rank. This outcome suggests that academic ability, at least as measured by standardized tests, is not associated with beauty. Our finding that the beauty of White women's and non-Whites of either gender is not correlated with the rank of the college they attended in the US suggests, moreover, that academic ability in general, not only as measured by standardized tests, but also including that measured by grades, letters of recommendation, is also not necessarily associated with beauty. This lack of correlation for White women and non-Whites of either gender suggests that the beauty premium we find for White men is the result of non-academic factors which might specifically benefit White men in the admissions process.

An important question for the validity of our positive results for White men in the US is whether there was self-selection into social media by beauty. It is beyond the scope of this study to address this question directly. However, we have a number of benchmarks groups to help mitigate this concern. If men tend to self-select into social media by beauty and the rank of their college, we would also expect that they would in China. Similarly, we would also expect such self-selection for White women, non-White minorities, and White men at technology colleges in the US. But, the beauty rank of members of these groups do not exhibit a positive correlation with the college they attended. We know of no basis to suggest that only White men who attended non-technology colleges in the US would self-select according to their beauty on to social media. Hence, the possibility that our results for White men are driven by self-selection seems implausible, or at least, less plausible than other alternatives, which we discuss below.

Another potential issue with our data is reverse causality. We use photos of graduates from 2012. The corresponding photos could have been taken in 2012 or even later, and likely much later than the year in which the admission decision was made. Consequently, the rank of the college attended can potentially affect the beauty rank if the college rank increases salary, and salary increases beauty by rendering better grooming and clothing more affordable. Again, if the direction of causality were reversed, we should find a similar association between the college rank and beauty in China, where graduates of higher ranked colleges earn comparably higher salaries, or for White women, non-White minorities, and White men in technology colleges in the US. However, we find no such association for members of these other groups.

5.1 Favoritism to athletes and the beauty of White men

As to why better-looking White men in particular may be favored in the admissions process, a correspondence study in Israel offers a potential clue (Ruffle and Shtudiner 2015). They find a beauty premium for men only, and surprisingly, a beauty penalty for women. Notably, this beauty penalty was driven by firms using in-house HR personnel, who they also find, are almost always younger women. The authors infer that the bias against hiring more beautiful women is driven by female sexual jealousy.

Such a bias could also exist in the admissions process for elite colleges. The potential favoritism of teachers or admissions officers and alumni who interview candidates for better-looking male students can help explain our findings for men, especially if the interviewers tend to be female and White themselves, given a same-race bias among women (Hitsch, Hortaçsu, and Ariely 2010a).[18] This possibility of teacher or admissions interviewer bias for better-looking men is especially important for elite colleges, like Harvard, which rely heavily upon interviews in the admissions process, particularly for athletes (Arcidiacono, Kinsler, and Ransom 2019). However, there is no need to posit a pervasive self-serving taste-based discrimination on the part of the people involved in the admissions process to explain our results.

It is widely known and often openly acknowledged that colleges favor admitting athletes. For example, in one survey, 28 percent of four year college admissions directors in the US acknowledged using lower standards to admit athletes (Green, Jaschik, and Lederman 2011). Colleges do so because they benefit from favoritism to male athletes. High-ability athletes bring positive attention to their college by helping to win intercollege sports competitions. Such attention increases alumni donations (Anderson 2017; Meer and Rosen 2009), the number (McCormick and Tinsley 1987) and quality of applicants (Pope and Pope 2014; Tucker and Amato 2006), and allows the university to charge a higher tuition (Alexander and Kern 2009). Moreover, if HR managers at elite firms discriminate by athletic ability (Rivera 2011), colleges can improve their placement record by discriminating similarly in their admissions decisions.

[18] http://data.worldbank.org/indicator/SE.PRM.TCHR.FE.ZS

In the case of Harvard, recruited athletes are admitted with drastically lower academic standards. Such lower standards result in an admissions rate of 86% for recruited athletes, which is over 14 times higher than for students who are not recruited athletes. As a consequence, recruited athletes make up over 10% of the admitted class though they are 1% of the applicant pool. Importantly for explaining our findings, 70% of admitted recruited athletes at Harvard are White (Arcidiacono, Kinsler, and Ransom 2019).

Hence, the favoritism colleges show towards athletes can help explain why we find that White men are better-looking in higher ranked colleges in the US, especially at elite private colleges. Selecting for top-male athletes may also select for male beauty. The key factor which connects athletic ability and male beauty is prenatal exposure to androgens. The second-to-fourth digit length ratio (2D:4D) has been proposed as measure of prenatal exposure to androgens. A low 2D:4D ratio is associated with a large body size (Klimek et al. 2014), greater lean body mass (Schroeder et al. 2012), a more dominant personality (Neave et al. 2003), a greater propensity for risk taking (Apicella, Carré, and Dreber 2015), success as finance traders (Coates, Gurnell, and Rustichini 2009), and a higher level of facial masculinity (Pound, Penton-Voak, and Surridge 2009). Larger size, leaner body mass, greater risk taking, and more domineering personality likely confer advantages in competitive sports. Hence, it has been found that a low 2D:4D ratio is a predictor of athletic prowess and success in highly competitive sports (Coates, Gurnell, and Rustichini 2009; Hönekopp and Schuster 2010), including within the college varsity sports setting (Giffin et al. 2012). Therefore, a preference for admitting male athletes, especially for the most popular varsity sports, e.g., football and basketball, likely selects for these physical and psychological traits—as well as height. The selection for higher levels of these stereotypically male features likely increases with the rank of college, because higher ranked colleges can draw from a larger pool of applicants.

Though the digit ratio of competitive female athletes are also lower than non-athletes (Giffin et al. 2012; Hönekopp and Schuster 2010), there is little evidence to suggest that prenatal testosterone also contributes to the female facial attractiveness which we measure. We are unaware of any other organic connection between traditional female facial attractiveness and athletic ability. Hence, given the connection between male athletic ability and male beauty made by male androgens and the preponderance of White men among male athletes, the preference colleges show towards athletes can help explain our finding that only White males are better-looking at higher ranked colleges in the US, but not White females or minorities.

In addition to selection for better-looking men through the preference for athletes, universities may also implicitly select for better-looking men when they select for applicants with demonstrated leadership experience. Leadership contests among high school students may well be little more than popularity contests, and beauty increases popularity (Gu and Ji 2019). Moreover, athletic ability, height, a large lean body, facial masculinity, and a daring and domineering personality, may complement the stereotypically masculine traits of leaders in the West, and thereby, contribute to the charisma and confidence expected of leaders, especially among adolescents (Mobius and Rosenblat 2006). White students from rich families may be over-represented among applying students showing high leadership potential. White students from rich families are the majority at elite private high schools. Private high schools are smaller than public high schools and tend to have more leadership opportunities (Arcidiacono, Kinsler, and Ransom 2019). Thus, another potential reason why we find a significant correlation between the beauty of only White men and the rank of the college they attended is that White women and other racial minorities may be less able to exploit the favoritism colleges show towards students with leadership experience in the admissions process.

In summary, we do not find a significant correlation between the beauty rank of alumni and the rank of the college they graduated from for Chinese students of either gender, White women and non-White minorities of either gender, or for White men who graduated from technical colleges. In light of the previous finding that intelligence is not correlated with beauty, our finding would further suggest that beauty is not correlated with academic ability, as measured by college ranking. We do find a significant positive correlation between the beauty of White men and the rank of the college they attended, if they attended non-technical public or private colleges, with the strongest correlation for those who attended private colleges. We suggest that a potential channel of the college admissions contribution to the labor market beauty premium for White men may due the favoritism colleges show in the admissions process towards athletes or leaders of high school clubs. Our evidence suggests that the labor market beauty premium for men and women in China and for White women and non-White minorities of either gender in the West originates in the labor market, while that of White men may have a college admissions contribution.

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Figures

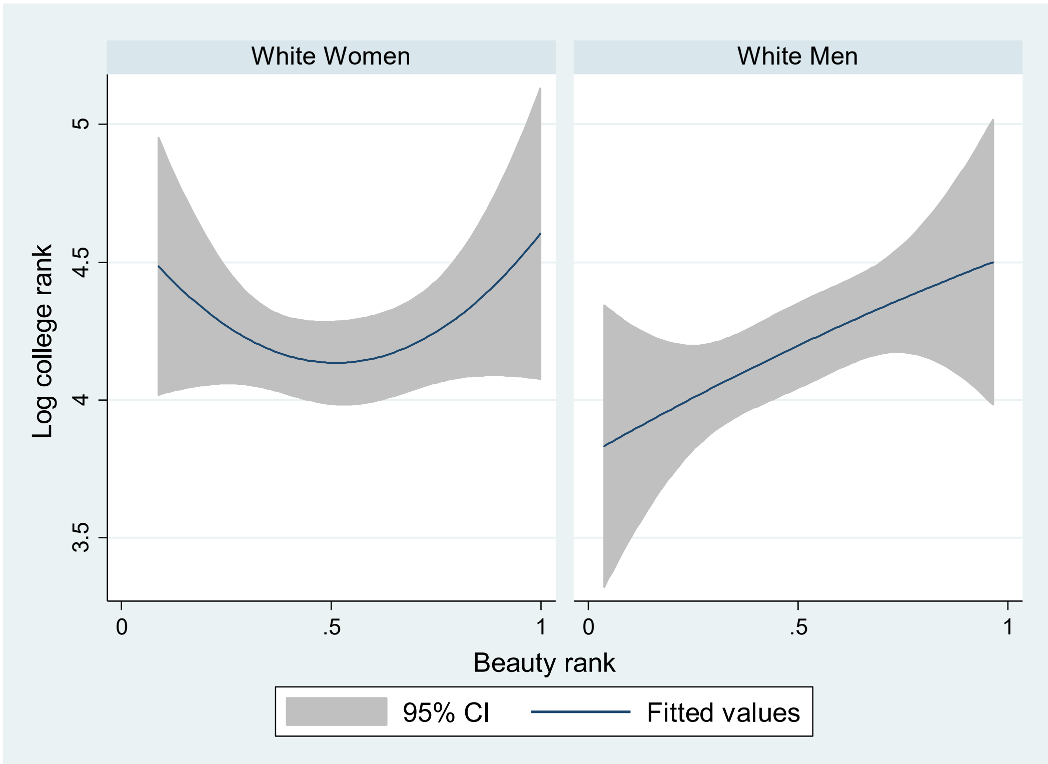

FIGURE 1: COLLEGE RANK VS. BEAUTY RANK FOR US WHITE WOMEN (LEFT PANEL) AND WHITE MEN (RIGHT PANEL)

7 Tables

TABLE 1: RACE AND AGE CATEGORIZATIONS FOR THE US SAMPLE

	Number of observations		
	Women	Men	Total
Race:			
White	329	331	660
Black	27	24	51
Hispanic	35	46	81
Asian	49	39	88
Unknown	10	10	20
Total	450	450	900
Age range:			
23–26	308	248	556
27 or older	142	202	344
Total	450	450	900

TABLE 2: SUMMARY STATISTICS OF PHOTO RATINGS

Rating	Obs	Mean	Std.Dev.	Min	Max
China Men	450	0.50	0.19	0	0.95
China Women	450	0.50	0.22	0	1
US Men:	450	0.50	0.20	0.05	1
White	331	0.52	0.20	0.05	1
Non-White	119	0.43	0.19	0.09	0.89
US Women:	450	0.50	0.20	0	0.95
White	329	0.52	0.20	0	.95
Non-White	121	0.45	0.19	0.04	0.93

Notes: Ratings are between 0 and 1, where the rating denotes the percentile of other photos that are less attractive. The max is not always 1 and the min is not always zero because of ties in the ratings of the most and least attractive, respectively.

TABLE 3: FIRST-STAGE REGRESSION

	Beauty Rating					
	(1)	(2)	(3)	(4)	(5)	(6)
Independent variables	US Men	US Women	US	China Men	China Women	China
Older than 27	-0.00	-0.05***	-0.03**			
	(0.02)	(0.02)	(0.01)			
Black	-0.04	-0.18***	-0.11***			
	(0.04)	(0.04)	(0.03)			
Hispanic	-0.04	0.01	-0.02			
	(0.03)	(0.03)	(0.02)			
Asian	-0.16***	-0.09***	-0.12***			
	(0.03)	(0.03)	(0.02)			
Display rank	0.00	-0.00	0.00	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Original random	-0.01	-0.03	-0.02	-0.00	-0.00	-0.00
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
Constant	0.52***	0.55***	0.54***	0.54***	0.54***	0.54***
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	450	450	900	900	900	900
R-squared	0.05	0.07	0.05	0.01	0.01	0.01

Notes: Subject's beauty rating, $0 \leq Rating_i \leq 1$, where 1 indicates highest rating, is the dependent variable. 'Older than 27' is a dummy variable which equals 1 if the subject is older than age 27 and 0, if the subject is between 23-26. Chinese subjects are always between 23-26 years of age in our sample. Black, Hispanic, and Asian are dummy variables which equal 1 if the subject is one of those races. 'Display rank' is rank of the subject in the search results, based on a random number chosen before the search. Higher rank number indicates lower position on the search page. 'Original random' takes on the value of 1 if the display rank number is based on the first draw and 0 if based on the second draw. Robust standard errors in parentheses: *** p<0.01, ** p<0.051.

TABLE 4: REGRESSION RESULTS FOR CHINA

	College Rank					
	(1)	(2)	(3)	(4)	(5)	(6)
	China Men	China Women	China	US Men	US Women	US
Beauty rank	0.08	-0.03	-0.03	0.64**	-0.02	-0.00
	(0.31)	(0.27)	(0.27)	(0.28)	(0.24)	(0.25)
Gender			-0.11			-0.50
			(0.42)			(0.38)
Gender*Beauty rank			0.11			0.50
			(0.41)			(0.37)
Constant	3.94***	4.05***	4.05***	3.47***	4.13***	4.11***
	(0.31)	(0.28)	(0.28)	(0.29)	(0.25)	(0.25)
Observations	450	450	900	450	450	900
R-squared	0.00	0.00	0.00	0.01	0.00	0.00

Notes: The dependent variable is $College\ Rank_i$ is the *log* of rank of the college that subject i attended. A lower number for the college rank implies greater prestige. Beauty rank is the subject's beauty rank, $0 \leq Beauty\ Rank_i \leq 1$, where lower number indicates greater attractiveness. Gender is a dummy variable which equals 1 if the subject is male and 0, if the subject is female. Robust standard errors in parentheses: *** p<0.01, ** p<0.051.

TABLE 5: REGRESSION RESULTS FOR THE US

	College rank					
	(1) Non-White Men	(2) White Men	(3) US Men	(4) Non-White Women	(5) White Women	(6) US Women
Beauty rank	0.42	0.75**	0.75**			
	(0.69)	(0.29)	(0.29)			
Non-White			-0.13			-0.26
			(0.43)			(0.37)
Non-White*Beauty rank			-0.33			
			(0.75)			
Constant				-0.18	0.04	0.04
				(0.62)	(0.25)	(0.25)
						-0.23
Observations						(0.67)
R-squared	3.68***	3.82***	3.82***	3.93***	4.19***	4.19***

Notes: The dependent variable is $College\ Rank_i$, which is the *log* of rank of the college (1-200) that subject i attended. A lower number for the college rank implies greater prestige. Beauty rank is the subject's beauty rank, $0 \leq Beauty\ Rank_i \leq 1$, where lower number indicates greater attractiveness. 'Non-White' is a dummy variable which takes on the value 1 if the subject is not White and zero otherwise. Robust standard errors in parentheses: *** p<0.01, ** p<0.051.

TABLE 6: REGRESSION RESULTS FOR THE US WHITE MEN

	College Rank							
	(1) Public	(2) Private	(3) Drop Top Private	(4) Drop Bot Private	(5) Public vs Private	(6) Non-Tech	(7) Tech	(8) Tech vs Non-Tech
Beauty rank	0.32**	1.74**	0.23*	0.78***	0.32**	0.84***	0.26	0.84***
	(0.14)	(0.75)	(0.13)	(0.29)	(0.14)	(0.32)	(0.63)	(0.32)
Private					-2.46***			
					(0.42)			
Private*Beauty rank					1.43*			
					(0.76)			
Tech								0.22
								(0.39)
Tech*Beauty rank								-0.58
								(0.70)
Constant	4.43***	1.97***	4.45***	3.79***	4.43***	3.78***	4.00***	3.78***
	(0.08)	(0.42)	(0.07)	(0.17)	(0.08)	(0.19)	(0.34)	(0.19)
Observations	256	75	283	319	331	265	66	331
R-squared	0.02	0.06	0.01	0.02	0.50	0.03	0.00	0.02

Notes: The dependent variable is $College\ Rank_i$, the *log* of rank of the college (1-200) that subject i attended. A lower number for the college rank implies greater prestige. Beauty rank is the subject's beauty rank, $0 \leq Beauty\ Rank_i \leq 1$, where lower number indicates greater attractiveness. Private is a dummy variable which takes on the value 1 if the subject attended a private college and zero otherwise. Tech is a dummy variable which takes on the value 1 if the subject attended a technology college and zero otherwise. Column (1) uses data only from public colleges. Column (2) uses data only from private colleges. Column (3) drops the top-4 private colleges. Column (4) drops the bottom-4 private colleges. Column (5) uses the full data set for White men and includes the private college dummy along with its interaction with beauty rank. Column (6) uses data only from non-technology colleges. Column (7) uses data only from technology colleges. Column (8) uses the full data set for White men and includes the technology college dummy along with its interaction with beauty rank. The control variables include the display rank (the position of the profile in the search result) and the age. Robust standard errors in parentheses: *** p<0.01, ** p<0.051.

TABLE 7: REGRESSION RESULTS OF STARTING SALARY ON COLLEGE RANK

	US Salary	
	(1)	(2)
	Mean	Median
Rank	-374.58***	-471.07***
	(107.36)	(130.14)
$Rank^2$	1.30**	1.65**
	(0.56)	(0.67)
Constant	72,991.31***	78,546.71***
	(3,903.65)	(5,173.70)
Observations	30	30
R-squared	0.46	0.50

Notes: The mean and median salary data is the salary of alumni in 2011 who enrolled in 2001 listed in A-Table 2. Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

8 Appendix

A-TABLE 1: EFFECT OF BEAUTY ON WAGES ACROSS COUNTRIES*

Country	Paper	Gender	Occupation	Wage effect: Above-average looks (%)	Wage effect: Below-average looks (%)	Notes
Canada & US	Hamermesh & Biddle (1994)	Men	General	5.4	-8.9	Stacked estimates
		Women		3.9	-5.5	
US	Mocan & Tekin (2010)	Men	General	10.8	-7	
		Women		4.5	-7	
United Kingdom	Harper (2000)	Men	General	Not significant	-14.9	
		Women		Not significant	-10.9	
Netherland	Pfann et al. (2000)	Both	Advertising Firm	18000 DFL increase in wage with average beauty changes from 10th to 90th percentile (assuming a 7.5% effect on wages averaging 150000 DFL per year)		Wage effect inferred from extraneous estimates
China (Shanghai)	Hamermesh et al. (2002)	Men	General	-	-	
		Women		17.9	-	
Brazil	Sachsida et al. (2011)	Men	Salesmen	Not significant	Not significant	
		Women		9	Not significant	
Germany	Doorley & Sierminska (2012)	Men	General	14	-	
		Women		20	-	
Luxembourg	Doorley & Sierminska (2012)	Men	General	-3	-	
		Women		10	-	
Australia in 1984	Borland & Leigh (2014)	Men	General	11.6	Not significant	
		Women		Not significant	Not significant	
Australia in 2009	Borland & Leigh (2014)	Men	General	Not significant	-12.9	
		Women		Not significant	Not significant	

* Reproduced from Liu and Sierminska (2015).

A-TABLE 2: RANK AND SALARIES FOR US UNIVERSITIES

Name	State	US News rank	Mean starting salary	Median starting salary
Harvard University	MA	2	$74,469	$87,200
Columbia University	NY	4	$75,676	$72,900
University of Pennsylvania	PA	8	$68,816	$78,200
Massachusetts Institute of Technology	MA	7	$83,418	$91,600
New York University	NY	32	$60,530	$58,800
Georgia Institute of Technology	GA	35	$43,259	$41,500
University of California-Davis	CA	38	$50,971	$57,100
Boston University	MA	42	$66,818	$67,000
University of Florida	FL	48	$53,141	$51,300
University of Texas–Austin	TX	53	$54,495	$52,800
University of Georgia	GA	62	$52,772	$46,500
University of Iowa	IA	71	$45,999	$48,700
University of Massachusetts-Amherst	MA	76	$51,204	$49,600
Stevens Institute of Technology	NJ	76	$75,347	$82,800
University of Vermont	VT	85	$37,139	$44,000
Florida State University	FL	95	$46,005	$44,000
University of Missouri	MO	99	$46,141	$46,000
University at Buffalo-SUNY	NY	103	$50,187	$49,700
University of Tennessee	TN	106	$42,580	$42,300
Illinois Institute of Technology	IL	116	$69,999	$68,200
University of Arizona	AZ	121	$43,698	$44,400
University of Arkansas-Fayetteville	AR	135	$46,247	$43,600
Oklahoma State University	OK	145	$45,431	$43,400
Texas Tech University	TX	156	$47,291	$46,100
San Diego State University	CA	149	$46,622	$48,700
New Jersey Institute of Technology	NJ	149	$64,065	$65,300
Mississippi State University	MS	156	$42,506	$39,600
University of Idaho	ID	166	$38,390	$39,900
University of Central Florida	FL	173	$46,925	$43,000
Southern Illinois University -Carbondale	IL	189	$42,740	$41,500

Notes: The mean and median salary data is the salary of alumni in 2011 who enrolled in 2001. The mean salary is the expected salary in 2011 calculated by The Economist, using a number of controls, based on data from the US Department of Education College Scorecard. We collected this data from The Economist magazine's website: *http://www.economist.com/blogs/graphicdetail/2015/10/value-university*

A-TABLE 3: WITHIN GENDER REGRESSION RESULTS FOR US NON-WHITES

Dependent variable	College rank							
	Non-White		Black		Hispanic		Asian	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Men	Women	Men	Women	Men	Women	Men	Women
Beauty rank	-0.177	-0.263	-0.441	-1.901	0.158	0.666	1.770	-0.321
	(0.668)	(0.625)	(0.839)	(1.629)	(1.172)	(0.963)	(1.155)	(1.027)
Observations	119	121	24	27	46	35	39	49
R-squared	0.001	0.001	0.007	0.039	0.000	0.009	0.050	0.003

Notes: The dependent variable is $College\ Rank_i$, the *log* of rank of the college (1-200) that subject i attended. A lower number for the college rank implies greater prestige. Beauty rank is the subject's beauty rank, $0 \leq Beauty\ Rank_i \leq 1$, where lower number indicates greater attractiveness. Black, Hispanic, and Asian are dummy variables which equal 1 if the subject is one of those races. Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1