College Admissions and the Labor Market Beauty Premium

DAVID ONG[1], MAN (AMANDA) XIE[2], AND JUNSEN ZHANG[3]

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Beautiful people earn more. Surprisingly, this premium is often larger for men than for women, and is independent of customer contact, e.g., even in software engineering. Overlooked is the possibility that beauty can influence college admissions. We investigate this academic contributor to the labor market beauty premium by sampling 1,800 social media profiles of students from universities ranked from 1 to 200 in China and the US. Chinese university admissions are based on standardized test scores. In contrast, US universities use also extracurricular activities and grades, which are not necessarily beauty-blind. Consistent with beauty-blind admissions, we find that the beauty of students and the rank of their school are uncorrelated in China. However, only White men are better-looking at higher ranked schools in the US. Our findings suggest that the surprisingly high and field independent labor market beauty premium found for men (who are mostly White) in the US can be an unintended side effect of using non-academic/high school extracurricular activities in elite college admissions decisions.

Keywords: beauty premium, labor market discrimination, college admission

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[1] Email: dvdong@gmail.com, phone: +86 755 2603 2655 Peking University HSBC Business School, University Town, Shenzhen, Guangdong, 518055, PRC

[2] Email: man.xie17@gmail.com, Department of Marketing, Warrington College of Business Administration, Bryan Hall 100, PO Box 117150, University of Florida, Gainesville, FL 32611-7150

[3] Corresponding author email: jszhang@cuhk.edu.hk, phone: +85239438186, Department of Economics, Chinese University of Hong Kong, Shatin, NT, Hong Kong, SAR, PRC

I. 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, not limited to those with extensive dealings with customers who might indulge a taste for beauty. (See Appendix I for a review of this literature and A-Table for a summary of the beauty premium for men and women across studies.) To explain these unexpected findings, a number of authors have proposed employer discrimination through human resource (HR) managers as a potential cause. However, overlooked is the possibility that the 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. Indeed, if HR managers do discriminate by beauty or its potential correlates in extracurricular activities (Rivera 2011), colleges can improve their placement record by discriminating by these same correlates in their admissions decisions. In fact, colleges seem to do precisely that when seeking talent in "leadership, performing arts, or athletics"[4] among high school students. Beauty may well contribute to the physical charisma or confidence (Mobius and Rosenblat 2006), which may be necessary for election to leadership positions among high school students, given that the voting public (Berggren, Jordahl, and Poutvaara 2010) and even economists (Hamermesh 2006) exhibit such a bias 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 also extracurricular activities and grades in the decision to admit students (Green, Jaschik, and Lederman 2011); we hypothesize that the beauty of students and the rank of their university in the US is positively associated (negatively correlated given that smaller numbers denote higher ranks). In contrast, Chinese universities use standardized test scores almost exclusively[5] to admit students (Yang 2014; Bai and Chi 2014; Li

[4] See, for example, the admissions brochure for Harvard: https://college.harvard.edu/sites/default/files/HarvardCollege_2015-16_web.pdf. "...Most of our students combine the best of both scholastic and extracurricular achievement. Personal qualities—integrity, maturity, strength of character, and concern for others—also will play an important part in our evaluations."

[5] 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.

et al. 2012). Despite the shortcomings of such admissions system in terms of the stress it imposes upon students (Cai, Lu, Pan, & Zhong, 2014), it is necessarily beauty-blind. In light of a recent large sample study with twins where no relationship between facial attractiveness and intelligence was found (Mitchem et al. 2015), we hypothesize that there would be no association between the beauty of students and the rank of their university in China.

Our hypothesis for China was confirmed; the beauty of Chinese students is not correlated with the rank of their school. Our hypothesis for the US was confirmed only for White men. In light of our finding in China, our finding in the US that White men are better-looking at higher ranked schools would suggest that those men are favored in the admissions process, e.g., by teachers, guidance counselors, or admissions officers. We discuss potential reasons why White men in particular would be affected by a beauty bias after the main results.

In summary, our evidence suggests an elite college admission contribution[6] to the labor beauty market premium for men (who are mostly White) in the US. This could be an unintended side effect of using non-academic/high school extracurricular activities in college admissions. This contribution could help explain the greater beauty premium for men found in prior studies in Western countries. Our findings are also important because they suggest a systematic bias in US elite college admissions.

II. Methodology

We selected 30 universities ranked from 1 to 200 in each of China and the US. Each selected school has similar rankings in at least two commonly used ranking systems. The rankings for US schools include the U.S. News & World Report Ranking[7], the Academic Ranking of World Universities (ARWU)[8], whereas the Chinese University Alumni Alliance Ranking (CUAA)[9] and the Wu Shulian's Chinese University Rankings[10] are for Chinese schools. The school rankings are shown in the A-Table 6 in Appendix I.

[6] There is little disagreement that graduates of elite institutions have higher incomes, although to what degree that higher income is from the greater selectivity of elite institutions for more productive individuals, or whether those institutions actually impart higher productivity is still a subject of continued research (Dale and Krueger 2002; Dale and Krueger 2014).

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

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

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

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

We randomly sampled 30 profiles (15 for each gender) for each school on Facebook, which has a 72 percent penetration rate among college students[11] in the US, and in China, through the social media site Renren[12], with a reported membership of 280 million in 2013. 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. To register on the two social media sites, name, gender, and email address or phone number are required. Renren also requires birth date and educational information (either high school or college). Furthermore, the educational information of a Renren account can be "verified" by a school IP address or the school 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 may also join common-interest user groups which are organized by workplace, school, or other categories. Users determine who can browse their pages or share their updates with their privacy settings. On both websites, users can make their profile "public," where anyone with a membership can see their profile, or "open to friends", where only "friends" can see their profile, or "private", where only they themselves can view their profile. Both websites allow us to search for public profiles with specific educational backgrounds.

Search engines generally use confidential proprietary algorithms to enhance the efficiency of searches. To avoid any unobserved influences from such algorithms on our results, we selected the profiles based upon random numbers from 1 to 200 generated prior to our searches. We drew two sets of random numbers; the second in case the profile indicated by the first number did not have the required information or photo quality. These criteria are available upon request. Each selected profile was of a student who graduated from the school as an undergraduate in 2012. The profile photo must be a clear color front-view photo without any head cover. Other people or backgrounds were cropped out to focus the photo on the face of the subject. We paid raters (5

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

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

RMB/100 pairs in China and 0.75 USD/100 pairs in the US[13]) to rate all profile photos using a proprietary beauty rating program, which they could access through a standard web browser.

In the rating program, each photo is randomly matched with 10 other photos of the same gender in the same country. 4,500 photo pairs are generated for each gender in each country. 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 asked raters to decide only which photo of the pair is better-looking. Such a judgment may be easier and more precise than assigning a number to how good-looking someone is based on a numerical scale. 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. Each rater rated 100 pairs of photos. The software then aggregates the ratings for each photo into a continuous number between 0 percent, for the least attractive, and 100 percent for the most attractive. For each photo, these numbers represent the share of other photos that reviewers on average found less attractive.

In the US, each photo was rated by 12−37 times by US raters, with a mean of 22 times. In China, each photo was rated by 12−28 times, with a mean of 20 times. Such rating frequencies are comparable to other studies (Deryugina and Shurchkov 2015). 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 HSBC Business School, Peking University 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 within the 23−26 age range because they rarely take time off before college, and hence, were not rated for age. Each rater was asked to categorize 100 photos in total. Each photo was categorized once each by three different raters. The final race and age categories of the photos are determined by the ratings of the 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.

The following equation is estimated for each country:

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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.

$$Rating_i = \alpha + \beta_1 Schoolrank_i + \beta_2 Displayrank_i + \beta_3 OriginalRN_i + \beta_4 Age_i + \varepsilon$$

Eq. (1)

where i is the index of individual students. $Rating_i$ is a number between 0 percent and 100 percent representing the aggregate rating given by the raters, the value of which denotes the share of other individuals who were found less attractive in the pairwise comparisons by the raters. $Schoolrank_i$ refers to the school rank within each country. Since higher prestige ranks correspond to lower rank numbers, a *negative correlation* between the beauty of students and the rank (in terms of number) of their schools implies a *positive association* between the school rank (in terms of prestige) and beauty. $Displayrank_i$ is the profile rank on the screen in search engine results. $OriginalRN_i$ is the dummy indicating whether the sampled profile uses the originally generated random number or a new random number because the profile indicated by the original random number did not have the required information or the photo quality. Age_i is the age range (23−26 or 27 and older), based on the listed age of the profile in China, and the age attributed by the raters in the US.

III. Results

The insignificant *school rank* (-0.005) in column (1) of Table 2 indicates

Observation I. There is no significant correlation between the beauty of students and the school rank in China.

The data is separated by gender since the correlation between beauty and ability can vary by gender. Columns (2) and (3) of Table 2 show that

Observation II. There is no significant correlation between the beauty of men or women and the school rank in China.

Similarly, column (1) of Table 3 for the US shows that

Observation III. There is no significant correlation between the beauty of students and the school rank in the US.

Moreover, column (2) and (3) of Table 3 show that

Observation IV. There is no significant correlation between the beauty of men (-0.0157) or women (0.00461) and the school rank in the US.

Trends can also vary by race. White men and women make up the largest part (660/900 = 73%) of the sample. Column (4) shows that *school rank* becomes significant for White and columns (5) and (6) shows that this is driven by White men.

Observation V. The beauty of White men (-0.049**), but not White women (-0.0130) significantly increases with the school rank in the US.

In contrast, Table 4 shows that

Observation VI. There is no trend for Blacks, Hispanics, or Asians in the US, either in aggregate as non-Whites, or as separate individual races, even when further separated into genders.

We find no significant nonlinear relation when a quadratic term of school ranks is included in any of the above regressions for either US or China.

IV. Discussion

We found that aggregating across genders, the beauty of students is unrelated to their school rank for both China (Observation I) and the US (Observation III). In both China (Observation II) and the US (Observation IV), the insignificance held when we separated by gender. However, in the US, White men (Observation V) are better-looking at higher ranked schools. We found no trend for non-Whites, either in aggregate or when separated into different races or genders (Observation VI). Our results indicate that the high labor beauty market premium for men (who are mostly White) in the US may partly reflect the use made by elite colleges of non-academic or high school extracurricular activities in college admissions[14].

[14] White men constitute the larger part of the population across all studies of the labor market beauty premium in the West.

There could in principal be endogeneity issues with our results due to self-selection into social media. However, self-selection into social media by better-looks alone is not sufficient to explain our findings for either country. Although self-selection into social media by better looks and gender can in principle explain our findings in the US, still left unexplained would be why such self-selection into social media, if it occurs in the US, is stronger for higher ranked than for lower ranked schools and for men more than for women.

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 found a beauty premium only for men, and surprisingly, a beauty penalty for women. Notably, this beauty penalty was driven by firms using in-house HR personnel, who they also found, are almost always younger women. The authors infer that the bias against hiring more beautiful women is driven by female sexual jealousy. The potential favoritism of teachers, who tend to be female[15], or admissions officers, for better-looking male students can help explain our findings for men, particularly if they are White themselves, given a same-race bias among women (Hitsch, Hortaçsu, and Ariely 2010). However, there is no need to posit pervasive self-serving taste-based discrimination on the part of HR managers to explain these findings.

As mentioned in the introduction, leadership contests among high school students may select for physically attractive men, as has been shown for adult voters in political elections and among economists. Moreover, the favoritism that colleges show athletes[16] may also select for more muscular and taller men with more masculine facial features, i.e., more traditionally attractive men. Favoritism towards high school leaders and athletes may contribute to the adolescent height premium in the adult wages of White men (Persico, Postlewaite, and Silverman 2004) and for White male athletes graduates when they enter the job market (Long and Caudill 1991; Henderson, Olbrecht, and Polachek 2006; Olbrecht 2009). These leadership and sports criteria may be more important at elite universities particularly for White men. These schools may have to resort to softer criteria that will allow them to select from a larger population of White male

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

[16] 28 percent of four year college admissions directors in the US acknowledge using lower standards to admit athletes (Green, Jaschik, and Lederman 2011). Such lowered standards may potentially be motivated by the increase in the number (McCormick and Tinsley 1987; Pope and Pope 2014; Pope and Pope 2009) and the quality of applications (Tucker and Amato 1993), the consequent increases in the tuition rates that the university can charge (Alexander and Kern 2009), as well increases in alumni donations (Martinez et al. 2010). These are the hypothesized consequences of the extra attention that winning sports tournaments can bring universities.

candidates who apply. White men may be in the best position to avail themselves of these preferred channels in the college application process, if they have a comparative advantage in winning either high school leadership contests or major athletic tournaments (e.g., because of cultural and height differences) against their main academic competitors, women (Fortin, Oreopoulos, and Phipps 2015; Voyer and Voyer 2014), and certain minorities (Hsin and Xie 2014) in academic areas, while at the same time maintaining good academic standing. The correlation between exceptional ability in extracurricular activities and beauty may also be insignificant for women, because of women's traditionally greater use of makeup. Furthermore, leadership positions are less congruent with traditional notions of femininity and female beauty, than for traditional notions of masculinity and male beauty.

V. References

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Tables

TABLE 1: RACE AND AGE CATEGORIZATIONS FOR THE US SAMPLE

	Number of observation		
	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: REGRESSION RESULTS FOR CHINA

Dependent variable	Beauty ratings (%)		
	(1)	(2)	(3)
	China	Men	Women
School rank	-0.005	-0.0139	0.00769
	(0.011)	(0.0154)	(0.0169)
Additional controls			
Display rank & Original RN	Y	Y	Y
Observations	900	450	450
R-squared	0.011	0.002	0.041

Standard errors in parentheses;
***p < 0.01, **p < 0.05, *p < 0.1

Notes: Column (1) is the regression for Chinese students, whereas columns (2) and (3) are separated by genders. The control variables include the display rank: the position of the profile in the search result; the original RN: whether the sampled profile uses the originally generated random number; and the age.

TABLE 3: REGRESSION RESULTS FOR THE US

Dependent variable	Beauty ratings (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
	US	Men	Women	White	White men	White women
School rank	-0.006	-0.0157	0.00461	-0.031**	-0.0488**	-0.0130
	(0.012)	(0.0175)	(0.0173)	(0.015)	(0.0210)	(0.0207)
Age	-2.433*	-0.247	-5.047**	-2.051	0.0536	-4.535*
	(1.384)	(1.935)	(2.038)	(1.602)	(2.239)	(2.394)
Additional controls						
Display rank & Original RN						
Observations	900	450	450	660	331	329
R-squared	0.006	0.003	0.017	0.013	0.017	0.024

Standard errors in parentheses;
***p < 0.01, **p < 0.05, *p < 0.1

Notes: Column (1) is the regression for the US students. Column (2) is for men, and column (3) is for women of all races. Column (4) is for White. Column (3) is for White men, and column (4) is for White women. The dependent variable is the beauty ratings by the US raters of the US profiles. The control variables include the display rank: the position of the profile in the search result; the original RN: whether the sampled profile uses the originally generated random number; and the age.

TABLE 4: WITHIN GENDER REGRESSION RESULTS FOR US NON-WHITES

Dependent variable	Beauty ratings (%)							
	Non-White		Black		Hispanic		Asian	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Men	Women	Men	Women	Men	Women	Men	Women
School rank	0.035	0.029	-0.010	0.058	0.002	-0.010	-0.072	0.044
	(0.030)	(0.032)	(0.061)	(0.055)	(0.055)	(0.061)	(0.063)	(0.057)
Age	-2.253	-4.823	-13.668*	0.523	-4.772	-7.493	3.630	-14.684**
	(3.608)	(3.762)	(7.687)	(7.343)	(7.298)	(7.580)	(5.204)	(6.850)
Additional controls:								
Display rank & Original RN	Y	Y	Y	Y	Y	Y	Y	Y
Observations	119	121	24	27	46	35	39	49
R-squared	0.029	0.030	0.211	0.081	0.048	0.057	0.089	0.129

Standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: Columns (1) and (2) are the regressions for US non-Whites. Columns (3) and (4) are the regressions for US Blacks. Columns (5) and (6) are the regressions for US Hispanics. Columns (7) and (8) are the regressions for US Asians. The dependent variable is the beauty ratings by all US raters. The control variables include the display rank: the position of the profile in the search result; the original RN: whether the sampled profile uses the originally generated random number; and the age.

Appendices

Appendix I. Related literature

A number of empirical studies have demonstrated a robust labor market beauty premium for workers around the world in various sectors beginning in the seminal work of Biddle and Hamermesh (1994). The several 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 (Becker 1971), where the discriminated characteristic, in this case, beauty, enters directly into the utility function; and statistical (Arrow 1973), where the observable characteristic, also beauty, is correlated with the characteristic that enters the utility function, e.g., good social skills, which is not so immediately observable. Both forms of discrimination apply to employers and customers alike. On the one hand, employers can merely like better-looking employees without believing that they are more productive, in which case, the discrimination is taste-based. On the other hand, they can use looks as an indicator of social skills which enhance productivity, e.g., promoting cooperative behavior among other workers, in which case, the discrimination is statistical. Similarly, customers, e.g., purchasers of fashion magazines, can derive utility directly from better-looking workers. Or, they can use beauty to infer other characteristics, e.g., competence in doctors, because of a possible statistical association between beauty and cognitive and non-cognitive skills.

From the inception of the literature, there has been a notably and surprisingly larger beauty premium/plainness penalty 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 of the amount of interaction with customers show little explanatory power on the cross-sectional beauty premium (Doorley and Sierminska 2015; Hamermesh and Biddle 1994). See A-Table 5 in Appendix I. 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 increase their wages. For example, intelligence, which is generally associated with productivity in most jobs, can potentially increase the skill with which flattering clothes are chosen, or it can be used to 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. Thus, more intelligent workers can appear more attractive, thereby earning higher wages, although they are not necessarily more physically attractive. Furthermore, customers may not derive utility from the exceptional intelligence of those workers. These customers could rather 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 basis for the labor market beauty premium exist. In addition to the identification problems, the gender difference in significance could 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, a number of researchers in the beauty premium literature have used CV correspondence in the studies of employers. These have been widely used to explore ethnic and gender discrimination (Bertrand and Mullainathan 2004). Such field experiments/correspondence studies with employers can decrease the effects of these confounds 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 (2013). With the exception of the pronounced premium for better-looking women in office support, receptionist, and customer service jobs, they determined that roughly the same positive premium for both genders across jobs, irrespective of the degree of customer contact. A significant premium across all four of the occupations was found in China, including areas such as software engineering, which has minimal customer contact (Maurer-Fazio and Lei 2015). As in Argentina, the premium was also noticeably higher for women than for men. As mentioned in the discussion section, a randomized resume correspondence study in Israel that only better-looking men were more likely to receive a callback to a job application, whereas better-looking women suffered a penalty, and even in jobs which, as they point out, beauty plays no obvious role: accounts management, budgeting, industrial engineering, and computer programming (2015).

However, despite the advantages of these CV correspondence studies over empirical studies, they still cannot rule out statistical discrimination for unobservable characteristics, e.g., beauty as a signal of social skills. Moreover, they cannot control for hiring by stereotypes, e.g., people who look like the actual engineers in engineering firms. Thus, despite the many positive findings on labor market discrimination by beauty, the existing literature have largely ignored the possibility that the beauty premium may begin before entry into the labor market[17]. The source of the beauty premium is important both to better understand labor market discrimination and also to better target antidiscrimination regulations based upon personal appearance, which has already been enacted in some states and proposed elsewhere (Hamermesh and Biddle 1994; Hamermesh 2011).

The advantage of our study with respect to identification problems in the empirical and CV correspondence study literatures is, we only look at the relation between beauty, as rated by impartial observers, and labor market productivity traits, as revealed by school 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 have concerns about unobserved productivity-related traits correlated with beauty. Thus, neither taste-based nor statistical discrimination by customers or employers are relevant to this study. Moreover, given that the profiles rated here are pre-labor market university students, they are also less likely to have systematically selected out of the labor market by gender and beauty.

There is a small economics literature on 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

[17] There are many studies 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 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, these studies 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.

point average becomes negative for males and insignificant for females when personality and grooming are controlled for (French et al. 2009). High school facial attractiveness 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). A lack of 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 are of single schools, or if not, they did not test for the effect of the graduating university's rank. Thus, they do not rule out that the beauty premium in earnings was due to a potential bias in the college application process.

A-TABLE 5: EFFECT OF BEAUTY ON WAGES ACROSS COUNTRIES[18]

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. (2003)	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	

18 Reproduced from Liu X, Sierminska E (2014) Evaluating the effect of beauty on labor market outcomes. Work Pap.

A-TABLE 6: US UNIVERSITIES

Name	State	US News rank
Harvard University	MA	2
Columbia University	NY	4
University of Pennsylvania	PA	8
Massachusetts Institute of Technology	MA	7
New York University	NY	32
Georgia Institute of Technology	GA	35
University of California-Davis	CA	38
Boston University	MA	42
University of Florida	FL	48
University of Texas–Austin	TX	53
University of Georgia	GA	62
University of Iowa	IA	71
University of Massachusetts-Amherst	MA	76
Stevens Institute of Technology	NJ	76
University of Vermont	VT	85
Florida State University	FL	95
University of Missouri	MO	99
University at Buffalo-SUNY	NY	103
University of Tennessee	TN	106
Illinois Institute of Technology	IL	116
University of Arizona	AZ	121
University of Arkansas-Fayetteville	AR	135
Oklahoma State University	OK	145
Texas Tech University	TX	156
San Diego State University	CA	149
New Jersey Institute of Technology	NJ	149
Mississippi State University	MS	156
University of Idaho	ID	166
University of Central Florida	FL	173
Southern Illinois University -Carbondale	IL	189

A-TABLE 7: CHINESE UNIVERSITIES

Name	Province	CUAA rank
Peking University	Beijing	1
Fudan University	Shanghai	3
Nanjing University	Jiangsu	8
Sun Yat-Sen University	Guangdong	14
South China University of Technology	Guangdong	18
Central South University	Hunan	19
Xiamen University	Fujian	22
Hunan University	Hunan	34
Lanzhou University	Gansu	36
Beijing Jiaotong University	Beijing	44
Southwest University	Chongqing	56
Beijing University of Post and Telecommunications	Beijing	61
Hohai University	Jiangsu	72
Donghua University	Shanghai	78
Fuzhou University	Fujian	84
Guangxi University	Guangxi	89
Shanxi University	Shanxi	95
Shenzhen University	Guangdong	105
Hainan University	Hainan	104
Taiyuan University of Technology	Shanxi	105
Jiangsu University	Jiangsu	133
Shanghai Normal University	Shanghai	136
North University of China	Shanxi	151
Qinghai University	Qinghai	139
Huaqiao University	Fujian	160
Guangzhou University	Guangdong	165
Harbin University of Science and Technology	Heilongjiang	167
Changsha University of Science and Technology	Hunan	170
Ji'nan University	Shandong	183
Lanzhou University of Technology	Gansu	190