Beauty and Academic Career

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ABSTRACT

We examine the impact of beauty on the academic career success of tenure-track accounting professors at top business schools in America, and show that beauty plays a significant role. Specifically, after controlling for gender, ethnicity, publication history, work experience, and quality of alma mater, more attractive professors obtain better first school placements post-PhD and are granted tenure in a shorter period of time. Interestingly, there is no incremental benefit of attractiveness for the career progression from associate to full professor. These findings are consistent with our conjecture that when the signal of an individual's potential is noisy, beauty becomes a proxy for an individual's intellectual ability and social competency. The role played by beauty in hiring and promotion diminishes when the individual's ability and competency become apparent over time.

Keywords: Beauty, accounting, career, labour market.

Beauty and Academic Career

I. INTRODUCTION

The value of beauty and its capacity for generating positive evaluations and impressions has long been the subject of discussion. A rapidly increasing body of literature in economics and sociology documents that beauty generates positive evaluations and impressions. In comparison with the less attractive, individuals with good looks are better liked (Walster, Aronson, Abrahams and Rottman, 1966; Kleck and Rubinstein, 1975; Feingold, 1990) and receive more favourable treatment in hiring, performance rating and promotion decisions ((Landy and Sigall, 1974; Dipboye, Arvey and Terpstra, 1977; Landy and Sigall, 1974). Studies in the fields of economics and management have explored the effect of beauty on business success and document an association with favorable traits of firms' top management (e.g., CEOs), such as confidence (Mobius and Roensblat, 2006) and happiness (Hamermesh and Abrevaya, 2013), which in turn contribute to higher shareholder values[1]. This widespread preference for physical attractiveness is commonly known as the "beauty premium" (Hamermesh and Biddle, 1994), and its potency is such that that even those who associate with beautiful persons gain in perceived stature (Sigall and Landy, 1973).

As previous studies have shown, the beauty premium exists in many social contexts and across a wide variety of professions, leading us to question whether it is caused by discriminatory or perceived valuable skills. On the one hand, physical attractiveness affects people's

[1] For example, Halford and Hsu (2014) document that firms enjoy higher returns around their announcement of hiring more attractive CEOs and higher acquirer returns upon acquisition announcements.

perceptions of intellectual competence and general mental health (Eagly et al., 1991; Feingold, 1992; Langlois et al., 2000; and Hosoda et al., 2003). Beautiful individuals are considered more socially competent (Miller, 1970; Dion, Berscheid and Walster, 1972; Eagly, Ashmore, Makhijani and Longo, 1991). On the other hand, the literature also shows the link between beauty and positive life outcomes to be largely discriminatory and driven by the favorable treatment from others (Dion, Berscheid and Walster, 1972; Hamermesh and Biddle, 1994; Mobius and Rosenblat, 2006). Given the mixed evidence, what drives the beauty premium remains a controversial issue.

It is this debate that motivates us to re-examine the question in a new, previously unstudied, setting. In this paper, we explore whether and how the beauty premium exists in academic career progression. Specifically, we examine whether beauty is associated with the quality of the first placement, the time to tenure, and the time from associate to full professor. There are several reasons to care about answers to this question. First, the vast majority of existing labor market-based beauty research is cross-sectional, focusing on the impact of beauty at a specific point in time. Little is known about the impact of beauty over the course of a person's career.[2] In this study, we extend the prior literature by assessing the impact of beauty on a professor's career progression. Second, compared to industry jobs, performance evaluation criteria in academia are relatively clear and objective making the hiring and promotion decisions less vulnerable to behavioral biases. If a "beauty premium" persists, this suggests that either academia is not as "fair" as we expect or the "perceived valuable skills" explanation dominates. Third, from the

[2] One notable exception is that of Sala et al. (2013), who use the Wisconsin Longitudinal Study data to assess the impact of facial attractiveness on people's socio-economic standing over one's life. The authors find that attractiveness matters for both genders and that its impact on occupational prestige is as important at the beginning of one's career as it is at the end of one's career, with no cumulative effects over one's working career.

perspective of PhD students and junior faculty members, while it is difficult to change their looks, understanding whether the bias exists and where it comes from can help them act to mitigate or avoid such biases.

We select accounting professors in US research institutions for this study, for several reasons. First, all PhD accounting programs in the US have a very clear mission of placing students to academic institutions. For this reason, each school only admits a few PhD students per year (i.e., usually between 2 to 4) and upon graduation, almost all accounting PhDs are placed at post-secondary educational institutions. This placement strategy differs markedly from PhD programs in science, engineering, and economics, where most graduates find jobs in industry, and mitigates the self-selection concern that the physical appearance of industry orientated PhD graduates differs systematically from those who remain in academia. Second, accounting is a well-structured discipline in business schools. Since teaching performance and research productivity are relatively easy to measure, the quality and quantity of research can be controlled more effectively. Finally, the relevant study and work experience of this paper's authors allows us a better understanding of the nuances involved in the hiring and promotion process.

We expect a positive association between beauty and indicators of academic success. An academic career is a long journey. The quality of the first placement, the smooth process to tenure, and the time it takes to be promoted to full professor all suggest success at different stages of one's career. However, a candidate's intellectual and social competencies are not readily apparent within a short time period. At the time of graduation, most newly minted PhDs do not yet have a top tier publication and much of their work has been under supervision of, or co-authored with, others. As such, typical signals, such as the supervisor's recommendation letter and the list of publications/working papers, could be very noisy proxies of one's research ability

and may drive hiring committees, consciously or unconsciously, to factor in attractiveness as a proxy for ability, resulting in more attractive candidates being placed at higher quality schools. After joining a school, the candidate's personal ability is revealed gradually over a number of years. The time it takes to resolve this uncertainty may vary across individuals, leaving the impact of beauty on *time to tenure* and *time to full professorship* an empirical question.

We download the photos and CVs of accounting faculty members from university websites for the *Businessweek* Top 50 2015 MBA School rankings, and the top 50 2015 Brigham Young University's (BYU) Research Publication rankings. We then supplement this list with accounting faculty from 31 lower tier US business schools, bringing our complete sample to 93 US business schools[3] yielding a total of 714 photo/CV combinations, from which we extract information concerning the variables we need to control for. These variables include education background, employment history, and information about publications and teaching. For each photo, we take advantage of M-Turk, an Internet sourced study participant pool run by Amazon.com, to rate photo attractiveness. We also use undergraduate and MBA business students from a major North American research university to rate these photos. Each photo is rated, on average, by 28 MTurk workers and 23 university students.

We first examine the association between beauty and the school ranking of a PhD candidate's first job placement. The school's ranking is based on i) *Businessweek* Top 50 MBA School rankings for 2015; or ii) Brigham Young University's (BYU) Research Publication rankings for

[3] These lower tier institutions include the schools that some faculty have ultimately moved to such as Auburn University, Case Western Reserve University, Miami University, Saint Louis University, and University of Tennessee. There are a number of *Businessweek* and BYU universities for which photos and CVs could not be obtained. These exceptions include South Carolina and Thunderbird for *Businessweek* rankings, and Temple, Florida International, Pittsburgh, Rutgers, Arkansas, and South Carolina for BYU rankings.

2015. After controlling for a number of personal characteristics and academic pedigree, we find a strong positive impact of perceived attractiveness on the school ranking of a PhD candidate's first job placement. In other words, more attractive PhD candidates are placed to more highly ranked schools. These findings support our conjecture that when a candidate's signal for quality is noisy physical attractiveness is used as a proxy for intellectual ability and social competency.

Next, we examine the association between beauty and time to tenure. Because tenure is not always achieved in one's first placement school, individuals are forced to move if they fail to meet the tenure requirement of their current schools. At the same time, it is likely that some individuals voluntarily move to other schools if they think they stand a better chance of getting tenure. Therefore, when examining the association between beauty and time to tenure, we consider three scenarios: i) when tenure is achieved at a professor's first school placement; ii) when tenure is achieved at a professor's second school placement when there is a voluntary early departure from the first school; and iii) when tenure is achieved at a professor's second or subsequent school placement and leaving the first school is a forced decision. We find that for scenarios i) and ii), there is a negative association between beauty and time to tenure. In other words, it takes less time for more attractive professors to achieve tenure. However, for scenario iii), we find that the time to tenure is not affected by their perceived attractiveness.

Further, we examine the association between beauty and the time to full professorship. Similar to the results for those professors who obtain tenure at their second or subsequent school, we find that the time to full professorship is not affected by beauty. These findings are consistent with the notion that sufficient time has passed for these individuals to demonstrate their ability. Physical attractiveness is no longer a proxy for ability and competency.

Our study contributes to economics and psychology literature in several ways. First, through studying the direct impact of attractiveness on career success in academia, we address the question whether the beauty premium is due to behavioral bias or perceived valuable skills. No study to date has explored the impact of physical attractiveness on initial job placement and career progression in tenure-track research positions. We are the first showing that when publication history is insufficient to reliably signal future research quality, hiring committees and tenure and promotion committees rely on attractiveness as a proxy for expected future potential. We are also among the first researchers to explore the differential impact of beauty over the course of a person's career. Early in the academic's career, the beauty premium is "alive and well". However, as their career progresses, the beauty premium disappears and is not a determinant of the promotion from associate to full rank professor. Remarkably, the market does not seem to correct for the pattern over time, as the same pattern observed for those professors obtaining tenure and full professorship in the 1980s and 1990s continues to be seen for those professors being promoted more recently in the 2000s. This finding is consistent with the notion that the beauty premium is more likely due to discriminatory bias and can be mitigated by less severe information asymmetry about people's skills.

Second, we take advantage of the progress in technology and improve our methodology. Only a handful of large-scale surveys have collected independent evaluations of physical attractiveness (Sala et al., 2013). Most rely on a single rating of a respondent's attractiveness either by the interviewer, the respondent, or a teacher. We add a new level of rigor to the literature, gaining more objective ratings of respondents' attractiveness by using photographs and having them rated, on average, by thirty unrelated individuals. This treatment is expected to reduce measurement noise significantly.

Third, our findings have important practical implications. While only a very small percentage of the population become tenure-track professors at America's business schools, a large percentage of the population is educated by these individuals. As such, prospective students would do well to know the differential impact of attractiveness in the selection and promotion of professors as attractive professors may not necessarily be better researchers and educators. Senior faculty should keep this in mind the next time they hire a rookie PhD or decide whether or not to grant tenure to an assistant professor. Aspiring PhD candidates should note that while they have little ability to change their attractiveness, it may have a significant influence on their career progression. While the benefits of beauty disappear in the latter stages of one's career, this may be "too little, too late" for less attractive professors as the benefit of obtaining an initial job placement at a top ranked school has long lasting effects.

The reminder of this paper is organized as follows. Section 2 discusses the related literature and develops the hypotheses. Section 3 describes data and research design. Section 4 presents the results of the empirical analysis. Section 5 concludes.

II. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

2.1 Background and Related Literature

Broadly speaking, there are two general perspectives on the observed relationship between attractiveness and success. These perspectives are: i) attractive individuals are "better" than their less attractive peers (i.e. smarter, socially competent); and ii) attractive individuals are no "better" than others and succeed due to discrimination on the part of society.

As an example of support for the first perspective, the empirical findings of Kanazawa and Kovar (2004) led them to reason that beautiful people are more intelligent when the following four conditions are present: 1) more intelligent men are more likely to attain higher status; 2)

higher-status men are more likely to mate with more beautiful women; 3) intelligence is heritable and 4) beauty is heritable. Large nationally representative samples from both the United Kingdom and the United States supply Kanazawa (2011) with additional evidence that attractiveness and general intelligence are positively associated. Mocan and Tekin (2010) find that unattractive individuals have a higher proclivity for committing crime. The authors suggest beauty may positively impact human capital formation since attractive individuals participate in more activities that build confidence and leadership skills. These skills, in turn, can lead to increased success in the labor market. Conversely, for unattractive individuals lack of human capital formation can lead to an increased likelihood of school suspension and a lower grade point average. Further support can be found in Feingold's (1992) meta-analysis of the literature, where social skills, freedom from social anxiety, opposite-sex popularity, and sexual experience are correlated with independent ratings of physical attractiveness (e.g. Lerner and Lerner, 1977; Pilkonis, 1977). More recently, in an experimental labor market where employers determine the wages of workers performing a maze-solving task, Mobius and Rosenblat (2006) find that 15% to 20% of the beauty premium is transmitted through higher self-confidence.

In terms of the second perspective, Dion (1973) finds that preschoolers discriminate differences in facial attractiveness, showing a distinct preference for attractive over unattractive children as potential friends. In another study by Clifford and Walster (1973), randomly selected fifth grade teachers evaluate a child's potential based only on the child's report cards and his/her photograph. The results confirm the researchers' expectation that physical attractiveness affects teachers' judgements in rating children's social potential and intelligence. Benson, Karabenick and Lerner (1976) make use of a novel research setting in which hundreds of graduate school applications are left in public phone booths in a large metropolitan airport. The applications only

differed in the photograph of the applicant attached to the application. As predicted, delivery of the application was facilitated more for attractive than unattractive persons.

Turning to academia, a few studies have explored the beauty effect in the classroom. Among them, Hamermesh and Parker (2005) find that moving from one standard deviation below to one standard deviation above the mean instructor attractiveness level is associated with a one standard deviation increase in the average class effectiveness rating.

Other studies find similar results in work settings. For example, Landry et al. (2006) investigate the influence of attractiveness in the context of several charitable fund-raising strategies, finding higher attractiveness of female solicitors is associated with both increased contributions and participation. Most recently, Ruffle and Shtudiner (2015) investigate the role of physical attractiveness in the hiring process. They send over 5000 CVs in pairs to approximately 2600 advertised job openings. For each pair, one CV is without a photo whereas the other one includes a picture of either an attractive or a plain-looking individual. Employer callbacks to attractive men are significantly higher than to plain-looking men and to men with no photos. Surprisingly, perhaps due to jealousy, attractive women did not enjoy the same beauty premium.

Overall, the findings provide consistent evidence that many benefits afforded to attractive individuals are discriminatory in nature, supporting the second perspective primarily and the first perspective to a lesser degree. Our brains seem genetically predisposed to subconsciously form an attractiveness stereotype, associating beauty with positive attributes. This phenomenon is commonly known as the "beautiful-is-good" halo effect of attractiveness (e.g. Miller, 1970; Dion, Berscheid and Walster, 1972; Langlois, 1986; Eagly et al. 1991; Feingold, 1992; Jackson et al, 1995). While a number of theories provide slightly different explanations for this

discrimination they are all broadly consistent with systematic biases of the mind (Kahneman, 2011).

2.2 Hypotheses Development

Humans are fundamentally social beings (Baumeister and Leary, 1995). We try to preserve the integrity of our social group and status when selecting new group members. Consider the impact of our evolutionary past on the inner workings of the brain, where many social interactions were brief and provided limited information. The same can be said of many social interactions we encounter in today's modern world. Not surprisingly, then, we often rely on first impressions to select new group members (Todorov et al., 2005; Bar, Neta and Linz, 2006; Willis and Todorov, 2006).[4]

At the time of completing a PhD, most graduates do not yet have a top tier publication and their work may be heavily influenced by mentors and senior co-authors. Recommendation letters from the graduate's thesis supervisory committee are typically favorably biased, making it difficult for prospective employers to assess a candidate's true potential. There is a significant amount of information asymmetry between the candidate and the prospective employer regarding the candidate's intellectual ability and research/teaching potential.

A significant component in the hiring process is the campus visit, where candidates present their thesis paper and meet individually with faculty members. A large part of the interview

[4] A famous example that highlights the rise in importance of appearance was the first presidential debate between Richard Nixon and John F. Kennedy. Following the presidential debates, radio polls favored Nixon while television polls predicted that Kennedy would win. Ultimately, Kennedy won the presidency with many pundits attributing the win to Kennedy's superior image on television; as Kennedy was not better than Nixon on the actual issues. Druckman (2003), in a controlled experiment, confirmed these claims using the original historical files and his students as listeners/viewers. While radio listeners were the only participants in his study to consider issue agreement when assessing leadership effectiveness, television viewers were the only participants to consider perceptions of integrity when evaluating these same candidates.

experience is "visual", much like that of a presidential candidate performing on television, and this is where attractive individuals excel. In their experimental setting using undergraduate students and local townspeople, Mulford et al. (1998) find that attractive individuals are advantaged in two ways; first, they have greater opportunity for social exchange; and second, these exchange opportunities are with others who have a higher propensity to cooperate once the interaction is consummated.

Consistent with findings in Cook and Mobbs (2016) in the context of the CEO selection, the PhD hiring committee will likely unconsciously factor attractiveness into their selection process. This leads to our first hypothesis:

Hypothesis 1: Individuals' facial attractiveness is positively associated with the school quality of the first job placement post-PhD.

Most schools allow assistant professors a period of five to seven years to obtain tenure.[5] Given that publication in a top tier accounting journal can easily take three to four years, from initial draft to final submission and approval, the tenure clock is rather short. Following the argument in the previous section, whether one's "true" research/teaching ability can be revealed within such a short time period remains an empirical question. In addition, most schools do not have a "rigid" written rule regarding the number of "A" publications required for tenure. This allows tenure and promotion committees a certain flexibility in their final decision. In light of the logic presented above, other qualitative considerations likely play a role in the tenure promotion decision.

[5] Considering a large portion of the final year is the formal review process i.e. putting together the tenure promotion package, obtaining reference letters from professors at different schools, and formal meetings by the faculty and tenure promotion committee, the real period of time is approximately four to six years.

This leads to our second hypothesis:

Hypothesis 2: Individuals' facial attractiveness is negatively associated with the time to tenure when tenure is achieved at a professor's first school placement.

Consistent with the findings by Fiske and Taylor (1991), we argue that the beauty effect is stronger when a direct measure of competence is absent than when it is present. Once a professor has already obtained tenure (i.e. on average, 10 years after first beginning PhD studies) or is seeking tenure at a second or subsequent school, much is known about the individual's past productivity and his/her prospects of future productivity i.e. quality and quantity of working papers. In light of such strong competency indicators, no reliance need be placed on beauty as an imperfect proxy.

In addition, and as argued by Cook and Mobbs (2016) in their paper on executive appearance and CEO selection, facial attractiveness for CEO candidates may only be an important distinguishing characteristic when candidates have similar skills causing firms to seek additional selection criteria. By the time a professor has tenure or is seeking tenure at a second or subsequent school, the pool of peers is sufficiently diversified in terms of publication history, working papers in the pipeline, and research interests.

As such, we have the following final set of hypotheses:

Hypothesis 3a: Individuals' facial attractiveness is not associated with the time to tenure when tenure is achieved at a professor's second or subsequent school placement.

Hypothesis 3b: Individuals' facial attractiveness is not associated with the time to full professorship since obtaining tenure.

III. SAMPLE SELECTION AND VARIABLES

3.1 Sample Selection

We obtain a list of schools featured in the *Businessweek* Top 50 MBA schools in the USA for the year 2015 and a list of those featured in the Top 50 Brigham Young University's (BYU) Research Publication rankings in the USA for the same year. These are provided in Appendix B. Due to data availability issues for a number of schools, our sample is restricted to 48 top rated *Businessweek* schools and 44 top rated BYU schools. We supplement this list with accounting faculty from an additional 31 lower tier US schools, bringing our complete sample to 93 business schools. We download the CVs and photographs of all professors at each of these schools who obtained a PhD in accounting and who are tenure-track or tenured faculty. We obtain current and historical school information, alma mater, gender, time to tenure, time to full professor, and number of years of non-academic working experience from each professor's CV. The publication history for each professor (as of June 2015) is pulled from three independent sources: (1) the professor's CV; (2) BYU's website: **http://www.byuaccounting.net/rankings/univrank/rankings.php**; and (3) manual collection of publication information for each of the top 6 accounting journals over the past 40 years. Any discrepancies are investigated and resolved. We obtain ethnicity information using a combination of visual photo inspection and/or background search of the surname. Assuming most individuals earn their undergraduate degree at age 22, we estimate professor age using the year the professor graduated from undergraduate studies. Finally, facial attractiveness is assessed using the ratings obtained from both student raters and Amazon Mechanical Turk workers, as detailed below. Our final sample includes 714 professors working at 48 *Businessweek* Top 50 MBA schools, 44 BYU Top 50 schools, and 31 lower tier US business schools.

3.2 Variables

3.2.1 Measures of Facial Attractiveness

Raw attractiveness scores are obtained from two independent sources, the first being the student raters who volunteered to participate in the rating tasks at one coauthor's university. For each student rater, a bonus mark was provided upon task completion. The second source is Amazon Mechanical Turk (MTurk), a crowdsourcing Internet marketplace that enables individuals and employers (known as Requesters) to coordinate the use of human intelligence to perform tasks. Employers post jobs known as HITs (Human Intelligence Tasks) and workers (called Providers or more colloquially Turkers) can then select jobs and complete tasks for a monetary payment set by the Employer. For each photo, both the student raters and the MTurk workers rate the attractiveness on two dimensions: (1) quantitative – on a scale of 0 (very unattractive) to 100 (very attractive); and (2) qualitative – as (a) below average; (b) average; (c) attractive; or (d) very attractive. To ensure accuracy, only Turk "masters" are used to rate the photographs. "Masters" are those individuals who have proven themselves in the marketplace as high quality workers.

Each photo is rated, on average, 28 times by MTurk workers and 23 times by student raters. The use of a composite rating is consistent with the work of Hamermesh and Parker (2005) and Sicinski (2009), who noted that the estimated coefficients on beauty are smaller when based on evaluations of a single rater rather than a composite measure. Composite measures are more reliable because they are based on aggregations of correlated responses. The actual number of ratings varies slightly from photo to photo because a random number generator is used to select photos for each rater.

The raw quantitative scores for each professor photo are then converted into a single attractiveness measure. First, the judge's mean rating across all photographs that he or she coded is used to minimize bias from "nice" or "harsh" judges.[6] Specifically, we subtract the mean quantitative score given by a rater from each quantitative score received from the same rater. This adjustment is required in order to account for the fact that each rater may have different benchmarks for beauty, which would add noise to the measure. Next, the highest and lowest rating for each photo is dropped and the average of the remaining mean-adjusted scores is taken. Finally, the variable is normalized (between 0 and 100) to facilitate the interpretation of regression coefficients.[7] We refer to this variable as the normalized quantitative facial attractiveness score (*Quant Score*). Given that accounting professors attract little if any attention in social media, it is highly unlikely raters would know the identity of individuals they are rating and as such we are unconcerned that familiarity will bias the results.

Since we are only able to collect the most recent professor photos from their institutions' or personal websites, it is likely that the photos may not represent the individual's looks at the time of their first job, tenure and full professorship respectively. Previous research shows there to be minimal cross-cultural variation in people's perceptions of which facial characteristics are considered attractive (e.g. Langlois et al. 2000; Perrett, May, and Yoshikawa 1994).

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

[7] Some researchers standardize the individual scores by subtracting the mean and dividing by the coder's standard deviation. We do not adopt this method because it could potentially reward "irresponsible" judges that predominantly assign the average rating and penalize those that followed instructions and used the entire scale.

Nonetheless, to adjust for the potential correlation of facial attractiveness with age, gender and ethnicity, we first regress the above mentioned *Quant Score* on an individual professor's age, gender and ethnicity. The regression model is as follows:

$$Quant\ Score_i = \beta_0 + \beta_1 Gender_i + \beta_2 Age_i + \beta_3 Ethnicity\_African_i + \beta_4 Ethnicity\_Asian_i + \varepsilon_i \qquad (1)$$

Definitions of all control variables are provided in Appendix A. Based on these coefficients we calculate the expected value of *Quant Score* for each individual professor in our sample. Our final measure of the quantitative facial attractiveness score *Beauty* is then calculated as the residual value of subtracting the expected *Quant Score* from the actual *Quant Score*.

As noted above, all photographs are obtained from the respective school's website and in all cases, the facial expression is either smiling or neutral (little variation), thus unlikely to affect the empirical findings. A study by Morrison et al. (2013) shows identity to be 2.2 times as important as emotion (anger, disgust, fear, happiness, sadness, surprise) in rating attractiveness for male and female pictures, suggesting that attractiveness is stable. Since the hard tissues of the face are unchangeable, raters are able to make attractiveness judgments based on structural cues.

We calculate the qualitative attractiveness measure as the average qualitative rating received for each professor. More specifically, we code "below average" as 1, "average" as 2, "attractive" as 3, and "very attractive" as 4. This alternative beauty measure deals with the concern that raters may provide different qualitative scores to professors. While we only report results using the residual value of normalized mean-adjusted quantitative scores in our main tests, all results are robust to the use of raw qualitative scores.

3.2.2. Control Variables

Since our empirical tests are designed to capture the relationship between attractiveness and career success, we control for characteristics likely to be correlated with (a) time to tenure and (b)

quality of first school placement in our multivariate tests. Our control variables include gender, ethnicity, prior non-academic work experience, quality of prior institutions, and number/quality of publications. Definitions of all variables are provided in Appendix A.

The regression equations for the hypotheses are as follows:

Hypothesis 1:

$$1stPlace\_Qual_i = \beta_0 + \beta_1 Beauty_i + \beta_2 Gender_i + \beta_3 Ethnicity\_African_i + \beta_4 Ethnicity\_Asian_i + \beta_5 WorkExpNumYears_i + \beta_6 PhD\_Qual\_Top5_i + \beta_7 PhD\_Qual\_Top20_i + \beta_8 Top6\_Asst_i + \beta_9 NonTop6\_Asst_i + \beta_{10} NonAcc\_Asst_i + \beta_{11} ImpactScore\_Asst_i + \varepsilon_i \quad (2)$$

Hypothesis 2/Hypothesis 3a:

$$NumYrsTenure_i = \beta_0 + \beta_1 Beauty_i + \beta_2 Gender_i + \beta_3 Ethnicity_{African_i} + \beta_4 Ethnicity_{Asian_i} + \beta_5 WorkExpNumYears_i + \beta_6 PhD\_Qual\_Top5_i + \beta_7 PhD\_Qual\_Top20_i + \beta_8 Asst\_Qual\_Top5_i + \beta_9 Asst\_Qual\_Top20_i + \beta_{10} Top6\_Assoc_i + \beta_{11} NonTop6\_Assoc_i + \beta_{12} NonAcc\_Assoc_i + \beta_{13} ImpactScore\_Assoc_i + \varepsilon_i \quad (3)$$

Hypothesis 3b:

$$NumYrsFull_i = \beta_0 + \beta_1 Beauty_i + \beta_2 Gender_i + \beta_3 Ethnicity\_African_i + \beta_4 Ethnicity\_Asian_i + \beta_5 WorkExpNumYears_i + \beta_6 PhD\_Qual\_Top5_i + \beta_7 PhD\_Qual\_Top20_i + \beta_8 Asst\_Qual\_Top5_i + \beta_9 Asst\_Qual\_Top20_i + \beta_{10} Assoc\_Qual\_Top5_i + \beta_{11} Assoc\_Qual\_Top20_i + \beta_{12} Top6\_Full_i + \beta_{13} NonTop6\_Full_i + \beta_{14} NonAcc\_Full_i + \beta_{15} ImpactScore\_Full_i + \varepsilon_i \quad (4)$$

IV. RESULTS

4.1. Descriptive Statistics

Table 1 presents the characteristics of the individuals in our sample. The number of observations in each regression varies with the availability of the variables included in the regression model. Our variable of interest, *Beauty*, has a mean value of 0.00 with a standard deviation of 9.40. It takes on average 6.46 years for an assistant professor to receive tenure and 6.35 years for an associate professor to be promoted to full professor. To mitigate the concern that the number of years to tenure and full professor may be highly skewed and the coefficients estimated using OLS model specification will be biased, we plot the distribution of number of years to tenure and full professor in Figure 1. From this figure, we notice that the distribution of years to tenure and full professor resembles the normal distribution, suggesting that skewness is not a concern.

Also reported in Table 1, around 71.3% of our sample observations are male professors. The average age when data is collected is around 48. In terms of ethnicity, 1.7% are African and 25.2% are Asian. The average work experience before they join academia is 2.11 years. In the year in which an assistant professor obtains tenure, the average number of publications in the Top 6 accounting journals is 3.36. This number increases to 5.82 in the year when associate professors are promoted to full professor. Correspondingly, the mean impact score of just tenured professors is 2.88. The same score is 3.02, on average, for professors who just received their full professorship.

Table 2 presents the summary statistics for beauty measures. Panel A reports the summary statistics for the number of ratings per photo, normalized mean-adjusted quantitative and raw qualitative beauty measures from both MTurk and student raters. On average, each picture is

rated by 28 MTurk raters and 23 student raters. The normalized mean-adjusted quantitative score from student raters is 50.93, slightly higher than 50.09 from the MTurk raters, while the raw qualitative score from student raters is 1.83, slightly lower than 2.02 from the MTurk raters.[8] Panel B reports the summary statistics of the mean-adjusted quantitative and qualitative beauty measures by gender, ethnicity group and age. On average, female professors receive higher scores than male professors. Non-Asian/African professors and younger professors also tend to be rated higher. To calculate the average beauty measure for each university, we require that the university has at least three accounting professors, from which we take the average. The construct of *Beauty* in our tables uses the pool of ratings from both MTurk raters and student raters combined.

4.2. The Effect of Facial Attractiveness on Quality of First School Placement

Appendix C presents the OLS regression results of (1). The results show that the coefficient on *Gender* is significantly negative with a value of -6.215 and a t-stat of -7.78, indicating that on average male professors receive lower facial attractiveness scores from the raters. Similarly, the coefficient on *Age* is also significantly negative, suggesting that raters assign lower scores to older professors. In terms of ethnicity, Asian professors, in general, receive a lower score as shown by a significantly negative coefficient (-3.567 with a t-stat of -4.31) on *Ethnicity_Asian*.

[8] Students, on average, rate photos significantly lower than MTurk workers. This is reflected in the lower raw scores for student ratings and is consistent with expectations, as student raters are significantly younger than MTurk raters. This bias is corrected with the normalized mean-adjusted quantitative scores as the mean-adjustment process corrects for bias at the individual rater level. Remarkably, the rank ordering of attractiveness ratings is consistent for student raters, MTurk raters, and the combined student/MTurk rater sample. As such, our findings are robust to the use of students raters alone, MTurk raters alone, or the combined student/MTurk rater population.

Table 3 reports the results of the test of H1. Columns (1) and (2) report the regression results from the ordered logit model specifications. Columns (3) and (4) report the OLS regression results. In Columns (1) and (3), the school rankings are based on the *Businessweek* Top 50 MBA School rankings from 2015. To mitigate the concern that our findings may be endemic to *Businessweek* rankings, we also conduct analysis based on Brigham Young University's (BYU) Research Publication rankings for the same year. These findings are reported in columns (2) and (4). The results show that the coefficient on *Beauty* is significantly negative in Column (1) (with a value of -0.026 and a p-value of 0.001), indicating that more attractive candidates tend to place at better quality universities when they graduate from their PhD program. This finding supports Hypothesis 1. The results are consistent with the OLS model specification and when BYU rankings are used, as shown in Columns (2) to (4). From the control variables, we note that the quality of first placement is influenced by the quality of the candidate's PhD program, as indicated by the significantly negative coefficients on *PhD_Qual_Top5* (with a value of -2.053 and a p-value of <0.001) and *PhD_Qual_Top20* (with a value of -1.119 and a p-value of <0.001). Interestingly, work experience helps PhD candidates place to better schools. The significantly negative coefficient suggests that the longer the PhD candidates worked, the better their schools ranked. In addition, the significantly negative coefficient on *Top6_Asst* (with a value of -0.540 and a p-value of 0.000) indicates that candidates who have publications in the top 6 accounting journals tend to have better placement when they graduate.

4.3. The Effect of Facial Attractiveness on Requisite Time to Attain Tenure

4.3.1 Professors who Attain Tenure at First School Placement

Table 4, Panel A reports the results of the test of H2; specifically, the OLS regression results of the association between facial attractiveness (*Beauty*) and number of years to obtain tenure (*NumYrsTenure*) when tenure is achieved at a professor's first school placement. The results show the coefficient on *Beauty* to be significantly negative (with a value of -0.028 and a t-stat of -3.07) in Column (1), indicating more attractive candidates obtain tenure at their first school placement in a shorter time period. The significant negative coefficient (with a value of -0.628 and a t-stat of -3.39) on *Gender* indicates male professors tend to obtain tenure faster than female professors. In addition, the significantly positive coefficient (with a value of 1.238 and a t-stat of 2.37) on *Ethnicity_African* indicates that candidates whose ethnicity group is African take longer to attain tenure. Professors from better quality universities tend to receive tenure faster, as indicated by the significantly negative coefficient (-0.909 with a t-stat of -3.73) on *Asst_Qual_Top5*. In addition, publications in both the top 6 accounting journals and non-top 6 accounting journals lengthen the time to tenure at one's first school placement. We find pre-hiring work experience is no longer significant to explain the requisite time to tenure.

Some professors voluntarily leave their first placement universities, perhaps to move to a better academic environment or for personal reasons. Table 4, Panel B reports the results of the test of H2 when tenure is achieved at a professor's first school or at a professor's second school placement when there is an early voluntary departure from the first school. The move is classified as an early voluntary departure if the number of years at the first school is less than or equal to three. Otherwise, it is treated as a forced departure. With the early voluntary departure cases included in the analysis, the sample size increases from 276 to 321. The results in Panel B are

similar to that in Panel A. The coefficient on *Beauty* is significantly negative in all four model specifications, indicating a shorter time period for attractive candidates to obtain tenure.

Overall, the results in Table 4 are consistent with our prediction in H1 that time to tenure is negatively associated with a professor's facial attractiveness when tenure is achieved at a professor's first school placement or second school placement in the event of voluntary early departure from the first school.

4.3.2 Professors who Attain Tenure at Second or Subsequent School Placement

Table 5 reports the results of the test of H3a; namely, the OLS regression results of the association between facial attractiveness measure (*Beauty*) and number of years to obtain tenure when tenure is achieved at a professor's second or subsequent school placement and leaving the first school is a forced decision. Similar to above, we classify the move as a forced departure if the number of years before leaving the first school exceeds three. Consistent with our prediction, the results show the coefficient on *Beauty* to be insignificant in all model specifications, indicating time to tenure is not associated with professor's facial attractiveness when tenure is achieved at a professor's second or subsequent school placement.

4.4 The Effect of Facial Attractiveness on Requisite Time to Become Full Professor

Table 6 reports the results of the test of H3b; specifically, the OLS regression results of the association between facial attractiveness measure (*Beauty*) and number of years to obtain full professorship from the time one first obtains tenure. Consistent with our prediction, the results show that the coefficient on *Beauty* to be insignificant in all model specifications, indicating time to obtain full professorship is not associated with the professor's facial attractiveness.

In summary, our findings suggest the behavior of hiring committees and tenure and promotion committees changes with the facial attractiveness of the candidate. At the time of

graduation from PhD studies, many hiring committees rely on attractiveness as a proxy for quality, resulting in more attractive candidates being placed at higher quality schools. This relationship continues to be observed in individuals obtaining tenure at their first school placement. For professors obtaining tenure at their second or subsequent school, and for those attaining full professorship, there is no observed impact of attractiveness.

4.5 Additional Analysis

Because the tenure and promotion process varies across universities, it is likely that the impact of beauty on the ability to obtain tenure is more pronounced in those schools where discretion during the tenure and promotion process is high. We therefore divide our sample into two subsamples based on the rigorousness of the tenure process and conduct analysis of the beauty effect on the tenure decision in each one.

Specifically, we look at two dimensions of rigorousness: (a) internal review rigorousness and (b) external review rigorousness. For internal review rigorousness, we hand collect information concerning the review process for tenure from each university. The amount of rigor is rated on a scale from 1 to 5, where 1 is the lowest rigor and 5 is the highest. Low (high) rigor characterizes those schools where the candidate's area department (independent professors and committees) does (do) the majority of the legwork to support promotion. For external review rigorousness, the amount of rigor is also rated on a scale from 1 to 5. Low rigor characterizes those schools that enable the candidate to (i) select large number of potential references, (ii) permit the candidate veto power or influence regarding references that should not be contacted, and (iii) permit the candidate's chair or department to pick all of the references exclusively. High rigor characterizes those schools where the candidate has little influence on the above-mentioned promotion-related activities. Finally, we develop an aggregate promotion rigorousness score,

where 1 is low rigor, 2 is moderate rigor and 3 is high rigor. Schools characterized by both high internal and external rigor are assigned a promotion rigorousness score of 3, while schools characterized by both low internal and external rigor are assigned a promotion rigorousness score of 1. The remainder are assigned a score of 2.

Table 7 reflects the results of the subsample analysis, with Panel A reporting the regression results of the association between beauty and number of years to obtain tenure when tenure is achieved at a professor's first school placement. Panel B reports the regression results of the association between beauty and number of years to obtain tenure when tenure is achieved at a professor's first school placement or second school placement when there is a voluntary early departure from the first school. Consistent with our predictions, the negative association between our beauty measure and number of years to obtain tenure is more pronounced in the less rigorous subsample across all model specifications, suggesting a correlation between greater judgmental discretion in the tenure and promotion process, and a high beauty premium.

V. CONCLUSION

Using human rater scores to proxy for the attractiveness of tenure-track accounting professors at 93 American business schools, and controlling for characteristics such as publication history, non-academic work experience, and quality of alma mater, we show that attractiveness has significant impact on a professor's career success, leading to better first school placements post-PhD and the attainment of a quicker route to tenure. This observed beauty premium is muted for those schools where the tenure and promotion process is more rigorous. Interestingly, however, there is no association between attractiveness and time to tenure for those professors who obtain tenure at their second school and for individuals when making the transition from the role of associate professor to that of full professor.

Our findings are broadly consistent with "beauty premium" findings from other studies; namely, that the "beauty premium" is mostly discriminatory in nature. While the extension of prior research findings to a different context may seem at first only an incremental contribution, we believe that we add much to the current literature.

First, and most importantly, we show that academics are prone to the same bias, so called beauty premium, as the rest of society. With a simple and clean setting, we demonstrate that such bias is mitigated and eventually disappears over the course of a person's career. Our study is the first to discover that the impact of attractiveness is contingent upon career phase/stage. While we cannot fully rule out other possibilities, such evidence is consistent with the conjecture that beauty is a noisy proxy for good talent and the beauty premium will disappear when information about people's talent becomes fully revealed. These insights contribute to our understanding of beauty and its role in our society.

Future research could examine whether the benefits of attractiveness apply in a similar way to academic success in other countries, where the relationship may be impacted by different cultural and social norms. Another interesting extension would be to focus on teaching schools and teaching-track positions within research-centric institutions to see if the same beneficial impacts of attractiveness are observed in this context. Future research could also investigate whether and to what extent we are learning from our known heuristic biases to avoid repeating prior mistakes. Given the plethora of previous research studies on attractiveness and the multitude of theories developed to explain this phenomenon, it is safe to say there are more interesting research topics yet to be explored.

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Appendix A
Variable Definition

Variable	Definition
1stPlace_Qual	School quality of the first placement, as per 2015 *Businessweek/BYU* rating of US schools (where 1 = top 5 school; 2 = 6th to 20th ranked school; 3 = 21st to 50th ranked school; 4 = 51st + ranked school)
NumYrsTenure	Number of years between first placement after graduation and promotion to tenured professor.
NumYrsFull	Number of years between associate to full professor.
Beauty	The measure of facial attractiveness of each professor's picture. It is calculated as the residual value of subtracting the expected *Quant Score* from the actual *Quant Score*. The expected Quant Score is calculated based on the coefficients obtained from $Quant\ Score_i = \beta_0 + \beta_1 Gender_i + \beta_2 Age_i + \beta_3 Ethnicity\_African_i + \beta_4 Ethnicity\_Asian_i + \varepsilon_i$ (1) Where actual *Quant Score* is the normalized mean-adjusted quantitative facial attractiveness score of each picture calculated from students' and MTurk workers' combined ratings. To calculate actual *Quant Score*, we start with the raw quantitative scores and make the following adjustments: 1) subtract the mean quantitative score given by a rater from each quantitative score received from the same rater; 2) drop the highest and lowest ratings for each photo; 3) calculate the average of the remaining scores for each photo; and 4) normalize the scores between 0 and 100 to facilitate the interpretation of regression coefficients.
Gender	An indicator variable equal to one if the professor is male; zero otherwise.
Age	Estimated professor age as of 2015. It is estimated using the year the professor graduated from undergraduate studies as a proxy for the year he/she turned 22.
Ethnicity_African	An indicator variable equal to one if the professor has African ethnicity; zero otherwise.
Ethnicity_Asian	An indicator variable equal to one if the professor has Asian ethnicity; zero otherwise.
WorkExpNumYear	The number of years of non-academic (industry) working experience.
PhD_Qual_Top5	An indicator variable equal to one if the school where professor obtained his/her PhD degree ranked as top 5, as per 2015 *Businessweek* rating (or BYU all publication ranking) of US schools; zero otherwise.

PhD_Qual_Top20	An indicator variable equal to one if the school where professor obtained his/her PhD degree ranked between 6th to 20th, as per 2015 *Businessweek* rating (or BYU all publication ranking) of US schools; zero otherwise.
PhD_ranking	The ranking of the school where professor obtained his/her PhD degree, as per 2015 *Businessweek* rating (or BYU all publication ranking) of US schools.
Asst_Qual_Top5	An indicator variable equal to one if the school where professor is an assistant professor ranked as top 5, as per 2015 *Businessweek* rating (or BYU all publication ranking) of US schools; zero otherwise.
Asst_Qual_Top20	An indicator variable equal to one if the school where professor is an assistant professor ranked between 6th to 20th, as per 2015 *Businessweek* rating (or BYU all publication ranking) of US schools; zero otherwise.
Asst_ranking	The ranking of the school where professor is an assistant professor, as per 2015 *Businessweek* rating (or BYU all publication ranking) of US schools.
Assoc_Qual_Top5	An indicator variable equal to one if the school where professor is an associate professor ranked as top 5 schools, as per 2015 *Businessweek* rating (or BYU all publication ranking) of US schools; zero otherwise.
Assoc_Qual_Top20	An indicator variable equal to one if the school where professor is an associate professor ranked between 6th to 20th, as per 2015 *Businessweek* rating (or BYU all publication ranking) of US schools; zero otherwise.
Assoc_ranking	The ranking of the school where professor is an associate professor, as per 2015 *Businessweek* rating (or BYU all publication ranking) of US schools.
Top6_Asst	Number of publications in Top 6 accounting journals, denoted as JAR, JAE, CAR, TAR, AOS, RAST, as of the year when becoming assistant professor.
NonTop6_Asst	Number of publications in non-Top 6 accounting journals, where accounting journals must be on Thomson Reuters Journal Citations Reports database, as of the year when becoming assistant professor.
NonAcc_Asst	Number of publications in non-accounting journals (i.e., economics, finance and management journals), where the journals must be on Thomson Reuters Journal Citations Reports database, as of the year when becoming assistant professor.
Top6_Assoc	Number of publications in Top 6 accounting journals, denoted as JAR, JAE, CAR, TAR, AOS, RAST, as of the year when becoming associate professor.
NonTop6_Assoc	Number of publications in non-Top 6 accounting journals, where accounting journals must be on Thomson Reuters Journal Citations Reports database, as of the year when becoming associate professor.

NonAcc_Assoc	Number of publications in non-accounting journals (i.e., economics, finance and management journals), where the journals must be on Thomson Reuters Journal Citations Reports database, as of the year when becoming associate professor.
Top6_Full	Number of publications in Top 6 accounting journals, denoted as JAR, JAE, CAR, TAR, AOS, RAST, as of the year when becoming full professor.
NonTop6_Full	Number of publications in non-Top 6 accounting journals, where accounting journals must be on Thomson Reuters Journal Citations Reports database, as of the year when becoming full professor.
NonAcc_Full	Number of publications in non-accounting journals (i.e., economics, finance and management journals), where the journals must be on Thomson Reuters Journal Citations Reports database, as of the year when becoming full professor.
ImpactScore_Asst	Mean impact factor of professor's publications as of the year when becoming assistant professor; where publications must be on Thomson Reuters Journal Citations Reports database.
ImpactScore_Assoc	Mean impact factor of professor's publications as of the year when becoming associate professor; where publications must be on Thomson Reuters Journal Citations Reports database.
ImpactScore_Full	Mean impact factor of professor's publications as of the year when becoming full professor; where publications must be on Thomson Reuters Journal Citations Reports database.

Appendix B
Top 50 School Rankings

Ranking	School Name		Ranking	School Name	
	Businessweek Rankings	*BYU All Publication Rankings (U.S. Schools in 2015)*		*Businessweek Rankings*	*BYU All Publication Rankings (U.S. Schools in 2015)*
1	Chicago	Stanford	**26**	Texas A&M	Texas at Dallas
2	Harvard	Texas at Austin	**27**	Ohio State	University of Washington
3	Pennsylvania	Southern California	**28**	South Carolina	UC, Berkeley
4	Stanford	Ohio State	**29**	Southern Methodist	Missouri
5	Northwestern	Pennsylvania	**30**	Georgetown	Notre Dame
6	Duke	Arizona State	**31**	Washington at St. Louis	Baruch College
7	Cornell	Texas A&M	**32**	Brigham Young	Arizona
8	Michigan	UIUC	**33**	Wisconsin	Pittsburgh
9	MIT	Indiana	**34**	Rice	Harvard
10	Virginia	Michigan State	**35**	Minnesota	Iowa
11	Carnegie Mellon	Chicago	**36**	Michigan State	Bentley
12	Dartmouth	UNC-Chapel Hill	**37**	Washington	Florida
13	Columbia	Georgia	**38**	Penn State	Kentucky
14	UC, Berkeley	Duke	**39**	Boston University	Rutgers
15	Indiana	Brigham Young	**40**	Illinois	Emory
16	New York University	Temple	**41**	Purdue	Pennsylvania State
17	North Carolina	New York University	**42**	Babson	Michigan
18	UCLA	Cornell	**43**	UC, Irvine	Alabama
19	Texas at Austin	MIT	**44**	Wake Forest	Arkansas
20	Notre Dame	Northeastern	**45**	Thunderbird	UCLA
21	Yale	Northwestern	**46**	Texas Christian	UC, Irvine
22	Emory	Florida International	**47**	Florida	South Carolina
23	Georgia Tech	Boston College	**48**	Boston College	Utah
24	Maryland	Columbia	**49**	Arizona State	Rice
25	Vanderbilt	Wisconsin-Madison	**50**	Rochester	Houston

Appendix C
The Association between Beauty and Individual Characteristics

This table reports the OLS regression results of *Quant Score* on individual characteristics. The full sample includes 714 individuals with available data. Variable definitions are provided in Appendix A. T-values are in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10% levels, respectively.

	Quant Score
Intercept	139.199***
	(23.59)
Gender	-6.215***
	(-7.78)
Age	-22.388***
	(-14.59)
Ethnicity_African	1.412
	(0.51)
Ethnicity_Asian	-3.567***
	(-4.31)
No. of Obs	714
Adj R-Sq	0.312

Table 1
Descriptive Statistics

This table presents the descriptive statistics on the measure of beauty and other control variables used in the main regression analyses. Variable definitions are provided in Appendix A.

	N	Mean	Std Dev	25th Pctl	Median	75th Pctl
1stPlace_Qual	714	2.798	1.053	2.000	3.000	4.000
NumYrsTenure	500	6.456	2.253	5.000	6.000	7.000
NumYrsFull	284	6.352	3.254	5.000	6.000	7.000
Beauty	714	0.000	9.396	-5.888	0.223	6.303
Gender	714	0.713	0.453	0.000	1.000	1.000
Age	714	3.868	0.237	3.664	3.871	4.078
Ethnicity_African	714	0.017	0.129	0.000	0.000	0.000
Ethnicity_Asian	714	0.252	0.435	0.000	0.000	1.000
WorkExpNumYear	714	2.111	2.886	0.000	1.000	3.000
PhD_Qual_Top5	714	0.162	0.369	0.000	0.000	0.000
PhD_Qual_Top20	714	0.272	0.445	0.000	0.000	1.000
Asst_Qual_Top5	500	0.166	0.372	0.000	0.000	0.000
Asst_Qual_Top20	500	0.226	0.419	0.000	0.000	0.000
Assoc_Qual_Top5	284	0.127	0.333	0.000	0.000	0.000
Assoc_Qual_Top20	284	0.232	0.423	0.000	0.000	0.000
Top6_Asst	714	0.434	0.763	0.000	0.000	1.000
NonTop6_Asst	714	0.056	0.242	0.000	0.000	0.000
NonAcc_Asst	714	0.115	0.441	0.000	0.000	0.000
Top6_Assoc	500	3.360	2.618	1.000	3.000	5.000
NonTop6_Assoc	500	0.458	0.987	0.000	0.000	1.000
NonAcc_Assoc	500	1.172	2.116	0.000	0.000	1.000
Top6_Full	284	5.817	3.987	3.000	6.000	9.000
NonTop6_Full	284	1.018	1.792	0.000	0.000	1.000
NonAcc_Full	284	2.606	3.467	0.000	1.000	4.000
ImpactScore_Asst	714	0.977	1.418	0.000	0.000	2.192
ImpactScore_Assoc	500	2.884	1.151	2.487	3.116	3.436
ImpactScore_Full	284	3.018	0.860	2.568	3.083	3.497

Table 2
Summary Statistics for Beauty measures

This table reports the summary statistics for beauty measures. Panel A reports the summary statistics for the number of ratings per picture, normalized mean-adjusted quantitative and raw qualitative beauty measures from both Mturk and student raters. Panel B reports the summary statistics of the mean-adjusted quantitative and raw qualitative beauty measures by gender, ethnicity group and age. ***, **, and * denote statistical significance at 1%, 5% and 10% levels, respectively.

Panel A

	No of ratings per picture	***Normalized Mean-Adjusted Quantitative***			***Qualitative***		
	Mean	Mean	Median	Std Dev	Mean	Median	Std Dev
All ratings	51	47.30	45.73	11.36	1.95	1.88	0.45
Mturk ratings	28	50.09	48.91	13.13	2.02	1.96	0.49
Student ratings	23	50.93	49.43	12.78	1.83	1.75	0.43
Difference:							
Mturk - Student		-0.84			0.19		
t-value		-2.26**			18.45***		

Panel B

	Normalized Mean-Adjusted Quantitative	***Qualitative***
By gender:		
Male professors	44.96	1.87
Female professors	53.12	2.16
Difference: male-female	-8.16***	-0.29***
By ethnicity:		
Asian/African professors	46.59	1.93
Non-Asian/African professors	47.56	1.96
Difference: A/F-non A/F	-0.97**	-0.03*
By age:		
Below 40	54.17	2.22
Above 40	44.24	1.83
Difference: Below 40 - Above 40	9.92***	0.39***

Table 3
The Association between Beauty and Quality of First Placement as Assistant Professor

This table reports the ordered logit (OLS) regression results of *1stPlace_Qual* (*1stPlace_Ranking)* on beauty measures. The full sample includes 714 individuals with available data. Variable definitions are provided in Appendix A. P-values (t-values) are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	1stPlace_Qual (Businessweek school) Ordered Logit	*1stPlace_Qual (BYU publications)* Ordered Logit	*1stPlace_Ranking (Businessweek school)* OLS	*1stPlace_Ranking (BYU Publications)* OLS
Intercept			36.395***	51.055***
			(-12.16)	(-8.77)
Beauty	-0.026***	-0.015**	-0.339***	-0.470*
	(-0.001)	(-0.046)	(-2.67)	(-1.77)
Gender	-0.347**	-0.227	-2.117	0.078
	(-0.027)	(-0.142)	(-0.81)	(-0.01)
Ethnicity_African	0.335	0.48	7.215	-1.921
	(-0.546)	(-0.378)	(-0.79)	(-0.10)
Ethnicity_Asian	0.185	0.286*	6.808**	11.106*
	(-0.261)	(-0.08)	(-2.48)	(-1.93)
WorkExpNumYear	-0.064**	-0.060**	-0.880*	-0.879
	(-0.023)	(-0.029)	(-1.89)	(-0.90)
PhD_Qual_Top5	-2.053***	-0.643***		
	(<.0001)	(-0.001)		
PhD_Qual_Top20	-1.119***	-0.389**		
	(<.0001)	(-0.016)		
PhD_ranking			0.258***	0.188***
			(-8.64)	(-5.34)
Top6_Asst	-0.540***	-0.454***	-7.742***	-12.123***
	(-0.000)	(-0.001)	(-3.32)	(-2.49)
NonTop6_Asst	0.312	0.305	3.494	17.019
	(-0.321)	(-0.324)	(-0.67)	(-1.56)
NonAcc_Asst	-0.134	0.189	-4.577	6.857
	(-0.543)	(-0.382)	(-1.25)	(-0.90)
ImpactScore_Asst	-0.034	-0.031	-0.718	-3.324
	(-0.678)	(-0.694)	(-0.53)	(-1.18)
No. of Obs	714	714	714	714
-2 Log Likelihood	1734.463	1837.9		
Adj R-Sq			0.157	0.072

Table 4
The Association between Beauty and Number of Years to Obtain Tenure when Tenure is Achieved at a Professor's First School Placement or Second School Placement when there is a Voluntary Early Departure from the First School

This table reports the OLS regression results of *NumYrsTenure* on beauty measures. Variable definitions are provided in Appendix A. T-values are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10% levels, respectively.

Panel A Tenure is Achieved at a Professor's First School Placement

	(1)	(2)	(3)	(4)
	NumYrsTenure (Businessweek school) OLS	*NumYrsTenure (BYU publications)* OLS	*NumYrsTenure (Businessweek school)* OLS	*NumYrsTenure (BYU Publications)* OLS
Intercept	5.532***	5.470***	4.518***	5.312***
	(21.28)	(19.70)	(13.30)	(16.41)
Beauty	-0.028***	-0.021**	-0.025***	-0.021**
	(-3.07)	(-2.26)	(-2.71)	(-2.17)
Gender	-0.628***	-0.612***	-0.553***	-0.648***
	(-3.39)	(-3.15)	(-2.95)	(-3.37)
Ethnicity_African	1.238**	1.478***	1.313**	1.408**
	(2.37)	(2.66)	(2.47)	(2.56)
Ethnicity_Asian	-0.032	0.035	-0.035	0.024
	(-0.16)	(0.17)	(-0.17)	(0.11)
WorkExpNumYear	0.003	-0.016	-0.012	-0.020
	(0.12)	(-0.56)	(-0.43)	(-0.68)
PhD_Qual_Top5	-0.687***	-0.194		
	(-2.84)	(-0.83)		
PhD_Qual_Top20	-0.102	0.113		
	(-0.54)	(0.57)		
PhD_ranking			0.003	0.000
			(1.48)	(-0.35)
Asst_Qual_Top5	-0.909***	-0.209		
	(-3.73)	(-0.85)		
Asst_Qual_Top20	-0.300	-0.186		
	(-1.53)	(-0.94)		
Asst_ranking			0.010***	0.002
			(3.78)	(1.13)
Top6_Assoc	0.113***	0.086**	0.133***	0.080**
	(3.43)	(2.48)	(3.84)	(2.34)
NonTop6_Assoc	0.270***	0.306***	0.315***	0.323***
	(2.89)	(3.08)	(3.33)	(3.30)
NonAcc_Assoc	0.118**	0.079*	0.094**	0.074
	(2.55)	(1.64)	(2.04)	(1.56)
ImpactScore_Assoc	0.093	0.068	0.108	0.091
	(1.29)	(0.89)	(1.46)	(1.16)
No. of Obs	276	276	276	276
Adj R-Sq	0.206	0.113	0.172	0.115

Panel B Tenure is Achieved at a Professor's First School Placement or Second School Placement when There is a Voluntary Early Departure From The First School

	(1)	(2)	(3)	(4)
	NumYrsTenure (Businessweek school) OLS	*NumYrsTenure (BYU publications)* OLS	*NumYrsTenure (Businessweek school)* OLS	*NumYrsTenure (BYU publications)* OLS
Intercept	5.555***	5.551***	4.611***	5.331***
	(21.84)	(20.51)	(14.28)	(17.97)
Beauty	-0.024***	-0.019**	-0.021**	-0.019**
	(-2.64)	(-2.09)	(-2.30)	(-2.03)
Gender	-0.733***	-0.697***	-0.656***	-0.725***
	(-4.05)	(-3.68)	(-3.60)	(-3.87)
Ethnicity_African	1.186**	1.401**	1.283**	1.371**
	(2.15)	(2.40)	(2.29)	(2.37)
Ethnicity_Asian	0.025	0.088	-0.026	0.055
	(0.13)	(0.43)	(-0.13)	(0.26)
WorkExpNumYear	0.005	-0.017	-0.015	-0.021
	(0.17)	(-0.56)	(-0.53)	(-0.72)
PhD_Qual_Top5	-0.497**	-0.123		
	(-2.10)	(-0.53)		
PhD_Qual_Top20	0.124	0.032		
	(0.67)	(0.17)		
PhD_ranking			0.003	0.000
			(1.39)	(0.30)
Asst_Qual_Top5	-1.094***	-0.194		
	(-4.41)	(-0.80)		
Asst_Qual_Top20	-0.347*	-0.242		
	(-1.79)	(-1.24)		
Asst_ranking			0.010***	0.002
			(4.21)	(1.45)
Top6_Assoc	0.109***	0.083**	0.131***	0.087***
	(3.46)	(2.52)	(3.98)	(2.65)
NonTop6_Assoc	0.288***	0.330***	0.308***	0.333***
	(3.22)	(3.52)	(3.41)	(3.56)
NonAcc_Assoc	0.152***	0.110**	0.131***	0.106**
	(3.34)	(2.33)	(2.88)	(2.25)
ImpactScore_Assoc	0.105	0.085	0.121*	0.099
	(1.49)	(1.13)	(1.68)	(1.33)
No. of Obs	321	321	321	321
Adj R-Sq	0.201	0.116	0.176	0.121

Table 5
The Association between Beauty and Number of Years to Obtain Tenure when Tenure is Achieved at a Professor's Second or Subsequent School Placement and Leaving the First School is a Forced Decision

This table reports the OLS regression results of *NumYrsTenure* on beauty measures. Variable definitions are provided in Appendix A. T-values are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	NumYrsTenure (Businessweek school) OLS	*NumYrsTenure (BYU publications)* OLS	*NumYrsTenure (Businessweek school)* OLS	*NumYrsTenure (BYU Publications)* OLS
Intercept	7.466***	7.519***	7.288***	7.643***
	(9.38)	(9.54)	(8.22)	(9.00)
Beauty	-0.016	-0.010	-0.013	-0.020
	(-0.66)	(-0.39)	(-0.54)	(-0.85)
Gender	-0.216	-0.299	-0.312	-0.342
	(-0.45)	(-0.64)	(-0.67)	(-0.73)
Ethnicity_African	-0.079	-0.238	0.035	0.066
	(-0.06)	(-0.19)	(0.03)	(0.05)
Ethnicity_Asian	1.149**	1.122**	1.134**	1.215***
	(2.43)	(2.35)	(2.41)	(2.60)
WorkExpNumYear	0.108	0.126	0.118	0.095
	(1.26)	(1.48)	(1.38)	(1.11)
PhD_Qual_Top5	-0.137	0.570		
	(-0.21)	(1.00)		
PhD_Qual_Top20	0.069	0.592		
	(0.15)	(1.13)		
PhD_ranking			-0.010*	-0.004
			(-1.71)	(-1.58)
Asst_Qual_Top5	-1.390**	-1.158**		
	(-2.35)	(-1.94)		
Asst_Qual_Top20	0.088	-1.135**		
	(0.15)	(-2.04)		
Asst_ranking			0.013*	0.001
			(1.80)	(0.41)
Top6_Assoc	0.129	0.110	0.104	0.063
	(1.36)	(1.20)	(1.11)	(0.68)
NonTop6_Assoc	0.237	0.287	0.305	0.343
	(0.79)	(0.98)	(1.01)	(1.17)
NonAcc_Assoc	0.129	0.133	0.132	0.145
	(1.12)	(1.14)	(1.15)	(1.25)
ImpactScore_Assoc	-0.134	-0.163	-0.170	-0.151
	(-0.62)	(-0.75)	(-0.78)	(-0.69)
No. of Obs	179	179	179	179
Adj R-Sq	0.036	0.037	0.034	0.019

Table 6
The Association between Beauty and Number of Years to Obtain Full Professorship

This table reports the OLS regression results of *NumYrsFull* on beauty measures. The full sample includes 284 individuals with available data. Variable definitions are provided in Appendix A. T-values are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10% levels, respectively.

	(1) *NumYrsFull* *(Businessweek school)* OLS	(2) *NumYrsFull* *(BYU publications)* OLS	(3) *NumYrsFull* *(Businessweek school)* OLS	(4) *NumYrsFull* *(BYU publications)* OLS
Intercept	14.588***	15.043***	14.462***	15.055***
	(14.20)	(14.62)	(11.63)	(13.26)
Beauty	0.011	0.013	0.018	0.017
	(0.41)	(0.48)	(0.65)	(0.62)
Gender	-1.207**	-1.252**	-1.300**	-1.403**
	(-1.96)	(-2.04)	(-2.14)	(-2.31)
Ethnicity_African	2.002	2.186	2.170	2.042
	(1.08)	(1.14)	(1.17)	(1.10)
Ethnicity_Asian	0.353	0.406	0.419	0.514
	(0.60)	(0.69)	(0.71)	(0.88)
WorkExpNumYear	0.051	0.043	0.039	0.037
	(0.61)	(0.52)	(0.47)	(0.45)
PhD_Qual_Top5	-0.101	-0.267		
	(-0.15)	(-0.40)		
PhD_Qual_Top20	0.208	-0.381		
	(0.40)	(-0.68)		
PhD_ranking			-0.006	-0.004
			(-0.85)	(-1.51)
Asst_Qual_Top5	-1.501*	-0.862		
	(-1.86)	(-1.17)		
Asst_Qual_Top20	-0.429	-1.187*		
	(-0.59)	(-1.68)		
Asst_ranking			0.007	-0.001
			(0.87)	(-0.45)
Assoc_Qual_Top5	-0.191	0.052		
	(-0.21)	(0.06)		
Assoc_Qual_Top20	-0.139	0.215		
	(-0.19)	(0.33)		
Assoc_ranking			0.003	0.004
			(0.41)	(1.06)
Top6_Full	0.005	-0.027	-0.021	-0.037
	(0.09)	(-0.44)	(-0.33)	(-0.61)
NonTop6_Full	0.300**	0.385**	0.348**	0.369**
	(1.96)	(2.52)	(2.29)	(2.42)
NonAcc_Full	0.054	0.025	0.052	0.055
	(0.78)	(0.36)	(0.76)	(0.81)
ImpactScore_Full	-0.537*	-0.586**	-0.619**	-0.669**
	(-1.84)	(-2.01)	(-2.08)	(-2.29)
No. of Obs	284	284	284	284
Adj R-Sq	0.049	0.043	0.042	0.046

Table 7
Rigorousness of the Tenure and Promotion Process

This table reports the OLS regression results of *NumYrsTenure* on subsamples based on the rigorousness of the tenure and promotion process. For internal review rigorousness, universities are less (more) rigorous when their internal review rigor score is less than (more than or equal to) 3. For external review rigorousness, universities are less (more) rigorous when their external review rigor score is less than (more than or equal to) 3. For promotion rigorousness, universities are less (more) rigorous when their internal review rigor score is equal to (not equal to) 1.Variable definitions are provided in Appendix A. T-values are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10% levels, respectively.

Panel A The Association between Beauty and Number of Years to Obtain Tenure when Tenure is Achieved at a Professor's First School Placement: Subsample Analysis

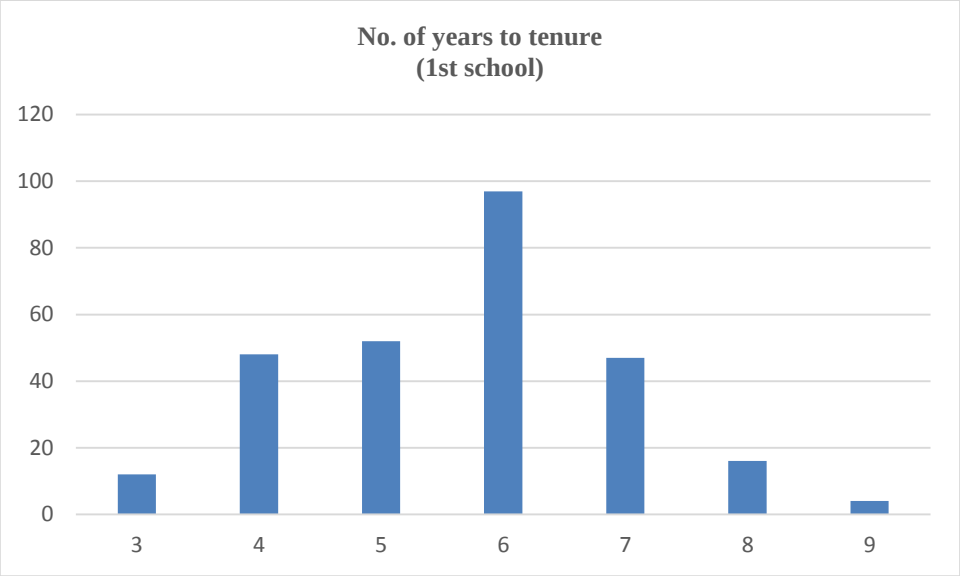
	Internal Review		*External Review*		*Promotion*	
	(1)	(2)	(3)	(4)	(5)	(6)
	More Rigorous	*Less Rigorous*	*More Rigorous*	*Less Rigorous*	*More Rigorous*	*Less Rigorous*
Intercept	4.708***	4.893***	3.810***	4.868***	4.469***	4.985***
	(7.20)	(12.05)	(5.05)	(12.99)	(8.91)	(10.62)
Beauty	-0.032	-0.023**	-0.005	-0.030***	-0.020	-0.027**
	(-1.54)	(-2.30)	(-0.25)	(-3.10)	(-1.24)	(-2.53)
Gender	-0.325	-0.607***	-0.151	-0.645***	-0.452	-0.559**
	(-0.77)	(-3.01)	(-0.37)	(-3.13)	(-1.49)	(-2.36)
Ethnicity_African	1.459	1.309**	1.739	1.277**	1.546*	1.302*
	(1.32)	(2.23)	(1.08)	(2.41)	(1.82)	(1.92)
Ethnicity_Asian	-0.129	-0.025	-0.102	0.108	-0.010	-0.010
	(-0.30)	(-0.11)	(-0.22)	(0.47)	(-0.03)	(-0.04)
WorkExpNumYear	-0.117*	0.034	-0.076	0.024	-0.071	0.030
	(-1.88)	(1.08)	(-1.15)	(0.77)	(-1.52)	(0.85)
PhD_ranking	0.001	0.003	0.011*	0.002	0.003	0.003
	(0.28)	(1.23)	(1.82)	(0.89)	(0.83)	(0.93)
Asst_ranking	0.021***	0.005	0.014**	0.009***	0.020***	0.003
	(3.29)	(1.51)	(2.29)	(3.08)	(3.84)	(0.91)
Top6_Assoc	0.179**	0.097***	0.206***	0.104***	0.204***	0.064
	(2.23)	(2.63)	(2.81)	(2.71)	(3.80)	(1.46)
NonTop6_Assoc	0.243	0.159**	0.108	0.243***	0.181	0.148*
	(1.20)	(2.12)	(0.50)	(3.21)	(1.15)	(1.84)
NonAcc_Assoc	0.080	0.045	0.130	0.057	0.058	0.056
	(0.74)	(1.03)	(1.05)	(1.35)	(0.66)	(1.24)
ImpactScore_Assoc	-0.110	0.151*	0.147	0.040	-0.027	0.175*
	(-0.76)	(1.86)	(0.83)	(0.54)	(-0.24)	(1.92)
No. of Obs	86	190	82	194	126	150
Adj R-Sq	0.185	0.135	0.118	0.189	0.200	0.126

Panel B The Association between Beauty and Number of Years to Obtain Tenure when Tenure is Achieved at a Professor's First School Placement or Second School Placement when There is a Voluntary Early Departure From The First School: Subsample Analysis

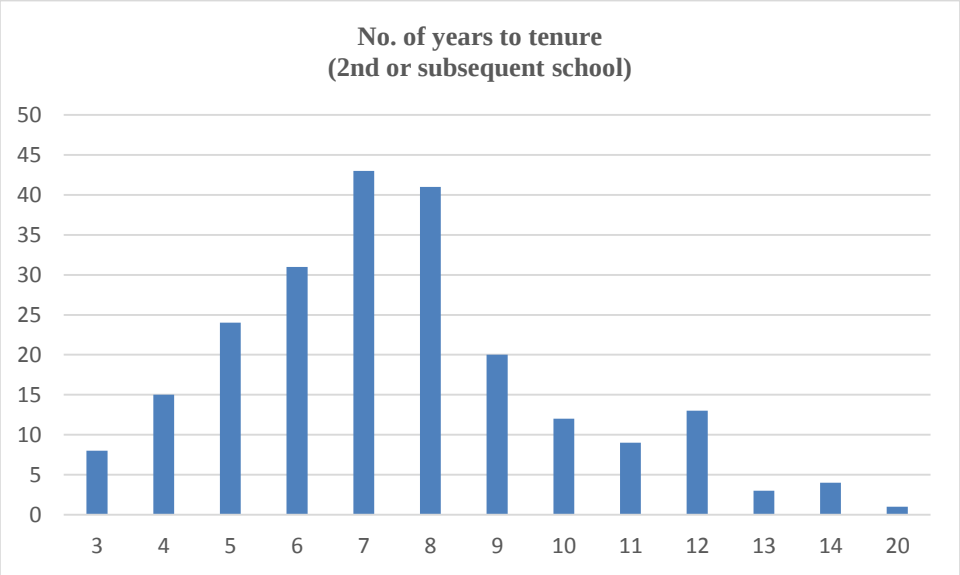
	Internal Review		*External Review*		*Promotion*	
	(1)	(2)	(3)	(4)	(5)	(6)
	More Rigorous	*Less Rigorous*	*More Rigorous*	*Less Rigorous*	*More Rigorous*	*Less Rigorous*
Intercept	5.042***	4.782***	4.080***	4.978***	4.650***	4.811***
	(7.80)	(12.78)	(6.19)	(13.60)	(9.65)	(10.91)
Beauty	-0.033*	-0.017*	-0.001	-0.026***	-0.019	-0.022**
	(-1.65)	(-1.72)	(-0.03)	(-2.64)	(-1.24)	(-2.04)
Gender	-0.649	-0.655***	-0.486	-0.636***	-0.679**	-0.531**
	(-1.64)	(-3.32)	(-1.25)	(-3.10)	(-2.34)	(-2.26)
Ethnicity_African	1.484	1.221**	1.700	1.221**	1.568*	1.226*
	(1.25)	(2.00)	(1.02)	(2.18)	(1.74)	(1.73)
Ethnicity_Asian	-0.027	0.008	-0.093	0.116	0.005	0.053
	(-0.06)	(0.04)	(-0.21)	(0.51)	(0.02)	(0.21)
WorkExpNumYear	-0.126**	0.032	-0.045	0.001	-0.059	0.019
	(-1.96)	(1.01)	(-0.71)	(0.03)	(-1.26)	(0.52)
PhD_ranking	0.003	0.002	0.008*	0.001	0.004	0.001
	(0.70)	(0.69)	(1.69)	(0.29)	(1.15)	(0.31)
Asst_ranking	0.013**	0.008***	0.014***	0.009***	0.016***	0.006**
	(2.18)	(3.13)	(2.79)	(3.08)	(3.51)	(2.01)
Top6_Assoc	0.132*	0.117***	0.182***	0.098***	0.182***	0.077*
	(1.81)	(3.32)	(2.69)	(2.64)	(3.55)	(1.86)
NonTop6_Assoc	0.240	0.192***	0.070	0.270***	0.173	0.209***
	(1.16)	(2.74)	(0.34)	(3.71)	(1.08)	(2.78)
NonAcc_Assoc	0.165	0.082**	0.159	0.095***	0.129	0.085**
	(1.52)	(2.34)	(1.40)	(2.70)	(1.50)	(2.34)
ImpactScore_Assoc	-0.029	0.150*	0.167	0.062	0.006	0.195**
	(-0.20)	(1.92)	(1.00)	(0.84)	(0.06)	(2.19)
No. of Obs	105	216	99	222	152	169
Adj R-Sq	0.117	0.171	0.144	0.180	0.168	0.155

Figure 1

Panel A Number of years to tenure if tenure is achieved at the first school



Panel B Number of years to tenure if tenure is achieved at the second or subsequent school



Panel C Number of years to full professor from time of obtaining tenure