THE PINHAS SAPIR CENTER FOR DEVELOPMENT
TEL AVIV UNIVERSITY

"Appearance and Gender Bias in Academia"

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Discussion Paper No. 7-15

April 2015

We would like to thank The Pinhas Sapir Center for Development at Tel Aviv University for their financial support.

This paper would have been impossible without instrumental help of Ishai Avraham, Emily Breza, Charles Norton and Yuri Sherman. We would like to thank Kelly Quinn, Christina Paxson, Nicole Tateosian and Deborah Donohue from proquest for providing institutional data. All views presented in this paper are those of the authors and do not represent the views of the Federal Reserve Bank of San Francisco or the Federal Reserve Board of Governors.

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Abstract

Are pretty women more likely to get a good job in male dominated fields? This paper explores how appearance and gender interact to affect labor market outcomes. Using unique data on PhD graduates from top Economics departments in the U.S., we are able to test whether better looking job candidates are more likely to get hired at top institutions and to publish better, and whether this likelihood depends on the gender of the candidate, on the gender composition of the field, and most importantly, on the interaction of appearance, gender, and the field's gender mix. We find that both women and men publish better when they are more attractive. However, while men's job placement does not depend on appearance, for women graduates there is an inverse U-shape relationship between attractiveness and the likelihood of getting a first job at a top ranking university. That is, if they are attractive, but not too much so. Moreover, we find that this result is stronger the higher the share of males within the research field, suggesting that men's appearance preferences play a role in the placement of women at top academic departments.

JEL classification: J16, J71, I23, M51

Key words: gender, beauty, appearance, economists, gender bias

1 Introduction

Do labor markets discriminate women on the basis of their appearance? There is now robust evidence of both appearance bias and gender disparities in the labor market. Less is known, however, about the interaction of appearance and gender. For one, there is mixed evidence on the importance of appearance for women relative to the importance of appearance for men (Hamermesh, 2011). But more importantly, no one has explored whether the appearance of women matters more in male dominated environments. If indeed the effect of women's appearance is stronger when the share of males is higher this may suggest that men's preferences regarding the appearance of women generate employment related outcomes for women.

To explore these interactions between gender and appearance in the labor market, this paper uses a unique data set of 750 ph.d graduates from 10 top economics departments in the U.S. together with rankings of their appearance, their publications and placement outcomes, and the share of males in their respective research fields. We ask whether the graduates' success in finding a higher ranked job and later in publishing papers depends on their appearance, whether the effect of appearance on success is stronger for women, and most importantly, whether the effect of appearance on success is stronger for women in male dominated fields. Our hypothesis is that women's looks matter more when men asses their appearance than when women do so.

We find that more attractive individuals publish better. For first job placement, appearance seems to affect only women: women get placed in a high rank academic institution if they are attractive but not too much so. Moreover, this inverse U-shape between women's attractiveness and their placement success is stronger when the woman's research field has a higher share of males.

Why would attractiveness matter for academic economists' success? Beauty matters in the labor market both because good looks are appreciated by co-workers, bosses and customers (Biddle and Hamermesh, 1998), and because being beautiful boosts an individual's confidence and charisma and hence her effectiveness in every aspect needing human interaction (Mobius and Rosenblat, 2006). Better looking people are therefore more likely to be hired and when hired - to get higher wages (Hamermesh and Biddle, 1994). Using data on academic publications we are able to move beyond the apparent wage premium and employer preference for beauty, to show that beauty also produces higher measurable outcomes. More attractive economists publish more papers and their papers have more citations. This could be because they are invited to more conferences, because they present their work more convincingly, and/or because they are sought after as co-authors.

Although all good looking scholars publish better, only for women does appearances matter for hiring. Evidence for gender gaps in hiring has been most convincingly conveyed by audit studies (Goldin and Rouse, 2000; Moss-Racusin et al., 2012) , where it was experimentally shown that women are less likely to get hired then men when gender is known relative to when gender is unknown. Here we find that the lower success in job placement for women is also related to appearance: attractive women are more likely to be placed in high ranking institutions than are plain-looking women and very attractive women. For men, on the other hand, attractiveness does not matter for hiring. Why would placement success increase non-linearly with attractiveness? If it was only that beauty enhances confidence and charisma, we should not expect such non-linearity. In particular, we would not expect that confidence and charisma wanes for highly attractive people. The decline in hiring success for very attractive women suggests there is a role for the demand for beauty. While co-workers may find attractive women pleasant, they might be intimidated by very attractive women, or hold some biases against them.

We therefore explore whether indeed demand factors affect the hiring of attractive women. To do so, we show that factors related to the environment - as opposed to the candidate's characteristics - matter for the probability an attractive women gets hired. Specifically, we show that the gender composition of the candidate's research field (within economics) matters. The effect of women's attractiveness on their placement success becomes stronger (stronger inverted U-shape) as the share of men in the applicant's research field increases. Thus, women's appearance matters more in male dominated fields. This suggests that men respond to women's looks (Guguen, 2012).

Finally, we are able to rule out a few of the mechanisms by which looks matter. We show that looking attractive is not related to being assessed as intelligent. Moreover, unlike attractiveness, looking intelligent does not predict placement or publication success. We also rule out that the gender interactions determine the productivity of beautiful people (such that beautiful women perform better in the vicinity of men) because we have publication data which directly measures performance, and we see that performance is not affected by gender interactions. Our results imply that gender interactions create other benefits to employers (such as joy in the presence of beautiful women).

We extend previous analysis on gender-based hiring bias by detecting a role for appearance on the gender gap in hiring. Thus, we show that the gender gap in hiring is more complex and layered than previously shown. Women are not only judged by men in a different way than they are by women, but their looks play an important role in determining their labor market success. The novelty of our work is in offering a setting that identifies sexual based gaps for women by estimating whether attractive women's outcomes are different than attractive men's outcomes in observational data.

In Section 2 we describe our data, in Section 3 we present our empirical approach and results, and in Section 4 we offer some concluding thoughts.

2 Data

Our data set contains information on all graduating students from ten of the top economics departments in the United States over the years 2002 to 2006.[1] For each graduate student we have graduation year, dissertation field, advisor's name and gender, and the student's career path upon graduation and 7 years after graduation. Career data includes the number and quality of publications, tenure status, institution, institution's rank, and the gender composition of faculty at those top economics department working in the graduate's field each year. Appearance data includes

[1]Choice of universities was dictated by data availability, and includes Berkeley, Chicago, Harvard, MIT, NYU, Northwestern, Penn, Princeton, UCLA and Yale.

the average attractiveness and intelligent-looking rating of the student's 2012 online photograph, as ranked by a random sample of evaluators.

2.1 Graduate students data

Our graduating student data for ten of the top economics departments in the U.S. was collected based on each institution's library catalogue of dissertations between the years 2002-2006. Whenever library data was unavailable, the data was collected from ProQuest's dissertation database. From the dissertations' titles we extracted data on advisors and field of research. Data on placement is based on institution's placement records and online search of CV's. For publication history we obtained the cumulative number of publications, the citations and the hc-index for each graduate student in each year in our data set using Harzing's Publish or Perish engine, which itself is based on Google Scholar search.[2] Ranking of economics departments was taken from McPherson (2012), with a rank of 1 indicating the most highly ranked department based on faculty's publications. The gender composition of faculty in each field-year cell was collected based on faculty lists provided by the ten institutions, coded by their field of research within economics.[3]

The Descriptive statistics for our sample are presented in Table 1. Our sample consists of all students who graduated from out top 10 institution during 2002 to 2006, for which we could find online photographs. There are 752 individuals of which 184 are women. Note this is the same share of women among all graduates in those top 10 schools during those years.

Five percent of our sample were hired by a top 10 top school and the mean ranking of the graduates' first job institution was 21. Seven years after graduation, the average institution ranking was 22.6, although some 40 observations were lost between the time of first job and 7 years later. Outcomes for first jobs were not statistically different for women graduates relative to men grad-

[2]The h-index gives a score of h to a scholar who has published at least h papers each of which has been cited in other papers at least h times. The hc-index, or contemporary h-index of citations adds an age-related weighting to each cited article.

[3]Fields were coded using JEL classification into the fields of Econometrics, Micro/Theory, Macro, International, Public, Labor, IO, Devel/Growth, Finance and Other.

uates. Overall, the hc-index 7 years after graduating was 6.87, and was 0.92 higher for men than for women, with this difference being significant at the 5 percent confidence level. The percent of men faculty within each field varies across economic fields from 72 to 95 percent, with the average being 85 percent.

Table 2 presents the distribution of PhD graduates across economic fields. Among graduates, men were significantly more likely to specialize in theory and finance, and women were significantly more likely to specialize in industrial organization.

2.2 Appearance ratings

Graduating students' photographs were collected online in 2011. Graduates were rated for how attractive they were and how intelligent they looked based on these photographs by 241 U.S. based workers of Amazon Mechanical Turk (AMT), an online marketplace for online workers. Each rater was referred to a password protected site, where she provided her age, gender, country of primary citizenship and years of education. The rater was then asked to rate the appearance of 50 individuals in our sample based on their photograph. Two questions were asked about each individual photographed: On a scale of 1 to 10 (1 - not at all 10 - very much), do you find this person attractive? Do you think this person is intelligent? We asked for these two different impressions, since it was not clear which dimension of appearance is the most relevant one for hiring bias. For a robust rating, we aimed for 15 opinions about each photograph. The names of photographed individuals was removed from the data, such that even the researchers do not know what ranking a specific individual received.

Summary statistics on raters is presented in Table 3. Half of the raters were women, the mean age was 33 and they had on average 15 years of education. Each of the AMT workers rated 50 photographs.

On average 14 raters viewed and rated each photograph. We used the average of the raw scores each photograph was given as the attractive appearance and intelligent appearance score for each graduate student. To capture the extent to which there was agreement on the appearance rating of each graduate, we also recorded the standard deviation of the scores given to the individual photographed.

Table 4 presents the average rating and the average standard deviation of the ratings. The mean scores for all graduates is 4.60. We see that men received on average a lower attractiveness score than women, with women rated 0.96 higher than men, almost one full mark higher. Moreover, there is also higher agreement among raters regarding the attractiveness of women, as reflected by the lower s.d. of attractive rating of women graduates relative to men graduates (1.91 for women vs 2.11 for men graduates). These results hold regardless of whether men or women do the rating: both men and women raters give higher attractiveness scores to women relative to men, and are more in agreement when rating women relative to men. Figure 1 depicts the distribution of attractiveness for men and women to illustrate that the whole distribution of attractiveness for women is shifted to the right relative to men's attractiveness distribution. This result stands in contradiction to the established finding that in the general population men are judged to be on average as attractive or good-looking as women(Hamermesh...). Our interpretation is that there is selection of graduate women in economics such that they are better looking on average than the economic graduate man. This could be because highly educated women take better care of their appearance than the average woman or because appearance matters more for women than men for academic success (either because women are screened based on their looks, or because their looks have brought them this far).

There is, however, a difference in the attractiveness ratings men and women give. Men raters tend to give more generous attractiveness scores than women raters do (4.71 vs 4.49, statistically significant at the 0.1% confidence level), and are more in agreement about their ratings than women raters are (as reflected by men's ratings lower standard deviation as compared to women's ratings, 1.9 vs 2.07). Moreover, this result holds regardless of whether they are rating men or women graduates.

The women in our sample are also rated as looking more intelligent than men on average. Whereas the average rating of looking intelligent is 6.7, women are rated 0.11 higher than men. Raters also agree more when rating women, with the s.d. of intelligent rating being 0.12 lower for women graduates relative to men. Both women and men raters tend to assign higher intelligence to women, and are more in agreement when doing so. There is a difference, however. Women raters tend to give higher intelligence scores, both to men and women graduates.

3 Empirical Analysis

3.1 Attractive scholars publish better

We begin our analysis by studying simple correlations between appearance and scholarly success, as measured by the record and impact of publications of people in our sample. Table 5 presents results of an ordinary least squares (OLS) regression analysis, in which we estimate the following equation

$$Publications_i = \alpha + \beta_1 Wom_i + \beta_2 Att_i + \beta_3 Wom_i Att_i + \mathbf{Z'}_i \gamma + \varepsilon_i, \tag{1}$$

Our dependent variable, $Publications_i$, is either the raw number of publications or the hc-index 7 years after graduation. The controls include the rank of the PhD institution, the rank of the first job, and field and year of graduation fixed effects.

Column (1) of Table 5 reports the estimation results of the equation above with no controls. The intercept of 4 is the average hc-index for the least attractive individual 7 years after graduating, and does not depend on the gender of the graduate. The coefficient on attractive is positive and significant at the 1% confidence level. An individual whose attractiveness score is larger than another's by 1 (on a scale of 1 to 10), has an hc-index which is 0.731 larger, or, an individual who is one standard deviation above another, has an hc-index which is higher by 0.2 standard deviation units. The result for women is not different than that for men.

In column (2) we add the rank of the PhD institution to absorb the quality of the PhD institution and possibly the individual's ability insofar as it is correlate with the rank of the PhD institution. As expected, the coefficient on the rank of the PhD institution is negative and significant. Recall that the top rank is 1, so that economists who graduate from an institution that is ranked one below another has an hc-index which is 0.245 below the other (or a 1 s.d. decline in the rank is associated with a 0.85 s.d. decline in the hc-index).

In column (3) we add the rank of the first job institution, and find a significant -0.045 coefficient. The first job is a good indicator for an individual's potential, at least as assessed by the market. Moreover, being placed in a good first institution also has implications for further success both in terms of prolific writing and publications. However, this relationship between first job rank and publications is 10 fold smaller than the relationship between PhD institution's rank and publications.

In column (4) we add dummy variables for the year of graduation. Although the hc-index is corrected for the researcher's academic age, we think age may still explain the hc-index and is possibly correlated with attractiveness. Indeed, graduating in later years is negatively correlated with publications even as measured by the hc-index. We further see that adding the academic age increases the coefficient on attractive to 0.97. This is because older graduates are perceived as less attractive. Column (5) adds field fixed effect to control for the possibly different ease of publications and citation behavior across economic fields. None of the field dummies is significant, and our coefficient on attractive doesn't change. Column (6) adds the number of publications, which is itself an outcome correlated with the hc-index. As expected it enters significantly, and reduces the coefficient on attractiveness as it too is positively correlated with attractiveness. In column (7) we add the intelligent appearance rating and see that the success of the graduates does not depend on how intelligent they appear, but only how attractive they are.

There are many potential reasons why attractiveness may matter for academic success. Attractive people may be more confident through years of positive feedback. They might be more charismatic when presenting their papers at conferences. Their company may be sought after as co-authors. A concern might arise that this correlation is not between the appearance of the individual and her academic success, but between the quality of the photograph and the academic success. It could be that better scholars are placed at higher ranked institutions where photographs are taken professionally for the best appearance. However, when we regressed appearance on the institution's rank (in year 7) we found that appearance is not related to the institution's rank, and thus should lessen such concerns. Another possibility is that more meticulous people have both better photographs and better papers. However, previous research has shown that the quality of photograph or the degree of primping has little influence on perceived beauty (Hamermesh et al., 2002).

3.2 Attractive women get good jobs

For first job placement we find that women's appearance matters while male's appearance does not. The distribution of attractiveness for men and women is depicted in Figure 2. On the left upper panel we see that men who don't get a first job at a top 10 school, attractiveness is normally distributed. For high achieving men, placed at a top 10 institution, attractiveness is somewhat skewed to the right. In the bottom panels we see the distribution of attractiveness for women. On the bottom left, low achieving women's attractiveness is taken from the whole distribution. However, there are no women in top 10 institutions who are less attractive or highly attractive.

To see the statistical significance of this observation we ran a logit model predicting the likelihood of the first job being a top 10 school. We are interested in whether attractive people get better jobs and whether attractiveness matters for women's placement in a different way than for men's. To allow for a non-linear effect of attractiveness we included quadratic terms in the regression,

$$Probability(y_i = 1|\mathbf{x}_i) = 1/(1 + e^{g(\mathbf{x}_i)}) \tag{2}$$

$$g(\mathbf{x}_i) = \alpha + \beta_1 Wom_i + \beta_2 Att_i + \beta_3 Wom_i Att_i + \beta_4 Att_i^2 + \beta_5 Wom_i Att_i^2 + \mathbf{Z}'{}_i\gamma + \varepsilon_i, \tag{3}$$

Where y_i is an indicator equal to 1 if the first job is at one of out top 10 economics department, and x_i consists of all the RHS variables explaining placement success.[4]

In Table 6 we present the results from the logistic regression. We find that although attractiveness does not matter for men's placement success, it does matter for women. A woman is more likely to get hired at a top 10 school if she is more attractive than if she is plain, but not if she is highly attractive. This inverse U-shape relationship between women's attractiveness and their likelihood of getting hired at a top 10 school remains significant at the 10% confidence level after we control for the rank of the students' PhD institution, the year they graduated, their field of specialization, and whether they appears intelligent.[5]

3.3 The demand for attractive women

We next investigate why there exists such an inverse U-shaped relationship between women's attractiveness and their first job placement success. Women's attractiveness could matter for hiring for one of two reasons. It could either be because attractive women are better scholars or because there is a demand for attractive women. We have already shown that the former is not the case. Both attractive men and attractive women publish better, and there is no differential productivity premium for attractive women.

Hence, we turn to test directly the role of demand on attractive women's hiring. To do so, we show that attractive women's placement success depends on the environment. We use the share of men in the candidate's field as a demand shifter. We test whether women's appearance matters more when there are more men in their research field at the time of graduation.

Specifically, we estimate a logistic regression model as in equation (2) where we augment $g(\mathbf{x}_i)$ with the share of men in the research field j, Sh_j. The differential demand for women's appearance is given by the interaction of the share of men in the field with the candidate's appearance and her

[4]This measure of placement success ignores placements at other top departments, but should not create biased estimates as long as there is no systematic difference between men and women in attaining other top jobs.

[5]In the next section we explore the sources for this relationship for women between attractiveness and success, and show that when we correctly control for the gender of the environment, the significance level increases.

gender.

$$g(\mathbf{x}_{ij}) = \alpha + \beta_1 Wom_i + \beta_2 Att_i + \beta_3 Sh_j + \beta_4 Wom_i * Att_i + \beta_5 Wom_i * Sh_j + \beta_6 Sh_j * Att_i + \beta_{\mathbf{7}} \mathbf{Wom_i} * \mathbf{Att_i} * \mathbf{Sh_j} + \mathbf{Z}'_i \gamma + \tag{4}$$

The results are given in Table 7. We see that for women, there is a stronger relationship between attractiveness and getting a top 10 job when the research field has more men. Figure 3 shows the estimated relationship between women's attractiveness and the probability of getting a top 10 first job for a range of share of males in the field. When the share of males in the field is at the sample low of 0.72, women's attractiveness is not related to a top 10 job. However, as the share of men in the field increases to the maximum of 0.95, the inverse U-shape relationship becomes stronger.

Our final set of results provides evidence on the role the gender composition of the environment plays in the success of attractive women, and hence provides evidence for sex-based demand for attractive women.

3.4 Robustness

3.4.1 The set of raters

First we explore whether the set of raters giving the attractiveness scores matters for the results we obtained. We want to know whether the results are robust to excluding non-reliable raters and whether the results depend on the gender of the raters. In Appendix Table A1-A3 we run our preferred specification for the three models of sections 3.1, 3.2 and 3.3 using various attractiveness scores. In column (1) we present our benchmark specification using the average of the attractiveness score given by all raters to each photograph. In Column (2) we use the average attractiveness score given only by reliable raters. We define reliable raters using a variation on cronbach's α. Specifically, we define a rater as reliable if the sum of square distance of each of his normalized rating from the mean rating by others is small. Columns (3) through (6) reports the results when appearance is rated only by women, only by reliable women, only by men or only by reliable men respectively.

In Table A1 we see that publications are predicted by attractiveness, regardless of the set of raters. The coefficient on attractiveness remains significant at the 1% level for all sets of raters. However, its magnitude declines when we use only women or men raters. In Table A2 we run the logistic model of 3.2, regressing the likelihood of finding a top 10 job on attractiveness. Our results are unchanged when we use only reliable raters. However, the coefficients on attractiveness of women decline and become insignificant when we use ratings by men or women only. In Table A3 we add the interactions with the share of men in the field. We can see that removing non reliable raters doesn't change the benchmark results, and that now the results remain even if we use only ratings by women, although the coefficients are smaller. Men raters do not seem to be doing a good job in predicting success of attractive women.

We can interpret our results as if basing the appearance assessment on more raters (both men and women) increases the accuracy of appearance rating and hence its predictive power. Yet, as we've seen from the standard deviation of ratings, women raters on average are more in agreement, and therefor their rating is more percise and has more predictive power.

3.4.2 Appearance aggregation

Next, we explore various methods for collapsing the raw attractiveness scores into a single measure. Our basic procedure is to measure the attractiveness of a graduate student as the average raw attractiveness score given by a set of raters. Averaging the scores given by different people assumes that there is universal understanding about what "1-not attractive at all" and "10-very attractive" refer to, as well as each score in between. Previous research (...) has shown that indeed there is almost universal agreement about how good looking people are.

However, evaluators may vary in their tendency to give high or low scores. For example, a score of 1 given by a tough rater may be more equivalent to a score of 3 given by a more lenient one. Hence, we might want to correct for individuals' tendency to give high or low scores. To do so, we re-scaled each rater's scores to reflect how high or low a given score is relative to his other scores. Since each evaluator rated 50 scores which were randomly and independently chosen from the sample, we assume each rater viewed photographs which were similarly distributed in terms of their appearance. In order to compare attractive appearance and intelligent appearance scores across AMT raters, we re-scaled the 1-10 score such that the new score is the percentile rank of the original appearance rating score within each AMT rater's score distribution. Thus, the scores of a rater who tends to give high scores can be compared to the scores of rater who tends to give low scores. The results hold using this re-scaled measure, and are reported in column (7) in Appendix Tables A1-A3. In column (8) we try another aggregation, normalizing each rater's score by demeaning them, and recaling by the rater's standard deviation of ratings. This would correct for rater's tendency to spread or compress her ratings. Such normalized appearance rating remains statistically significant in the first model predicting publications (Table A1, column 8). Yet, the normalized appearance rating loses its significance, or is reduced to 10% in the models predicting first job placement success. This could happen if the variance of an evaluator's ratings reflected the true variance of appearance of the photographs he was given. In such a case, the difference in the variance of ratings across raters reflect true differences and should not be corrected for.

3.4.3 Appearance and information

We would expect attractiveness would matter when other information about a worker's productivity is missing. Hence, as tenure and experience increases, a scholar's productivity can be more easily assessed through her publication records and we would expect the effect of attractiveness on job placement to wane. This is true because people place higher weight on their tastes and prejudices when the environment is more uncertain (....). Removing uncertainty regarding a candidate's ability, would therefor lead markets to place less weight on appearance, even if these are not merely tastes, but a good predictor of publications (which we've shown in section 3.1 is the case).

In accord with this prediction, we cannot find evidence that placement in later years is influenced by appearance for either men or women. When we regress the rank of the job in year 7 on attractiveness and gender, we find that rank is not statistically related to appearance. Although rank is related to publications, and (as we saw earlier) appearance affects the number of publications, appearance does not enter directly into the employment outcome 7 years after graduation.

4 Conclusion

This paper explored the role of scholars' appearance on their hiring and publication success. Our contribution is threefold. First, we show that appearance is related to academic productivity. While the literature has established that good looking workers are paid more, this is the first work to find market evidence for an actual productivity gain associated with good looks. Second, we find gender differences in how appearance affects labor market outcomes. We show that only for women does appearance matter for first job placement. Third, we show that women's appearance matters more in male dominated fields. This suggests there is a demand for pretty women by men. We interpret our findings as evidence for sexual based discrimination.

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Figure 1: Distribution of attractiveness of men and women

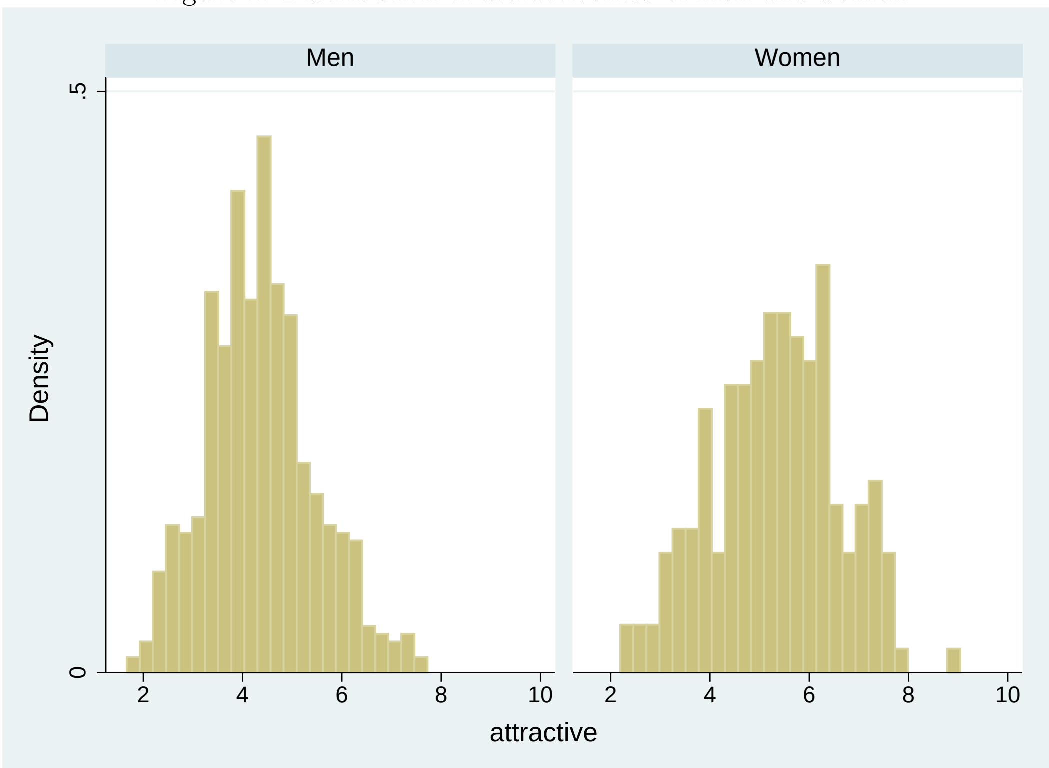


Figure 2: Distribution of attractiveness of men and women, by first job

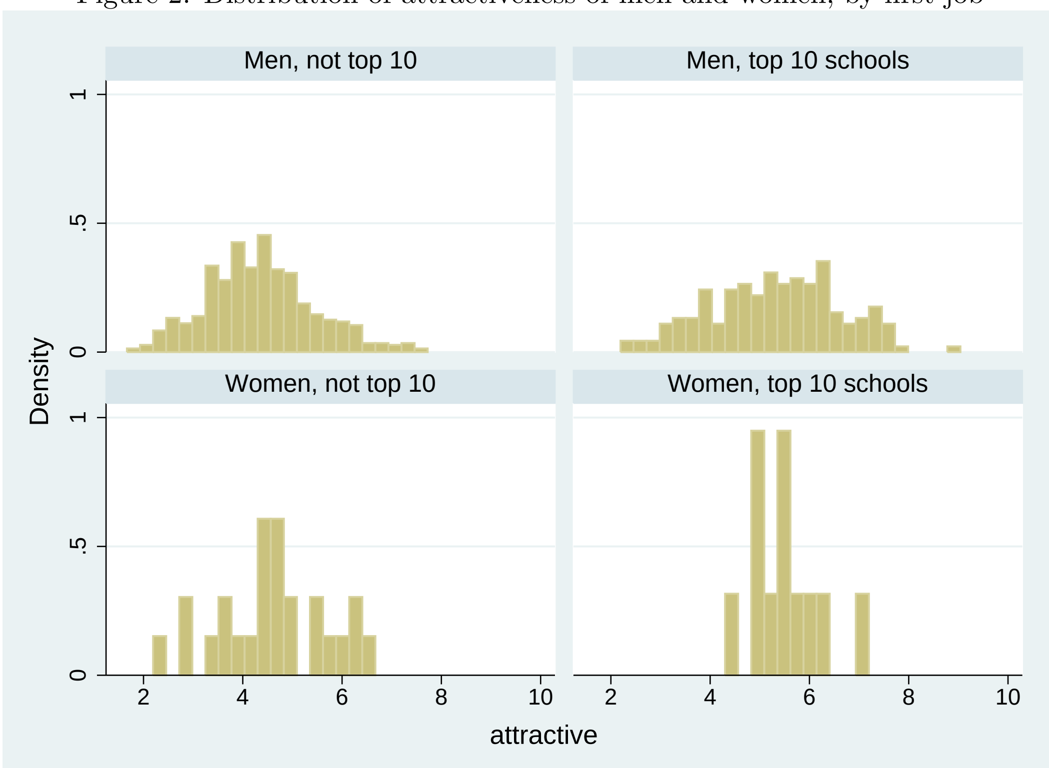
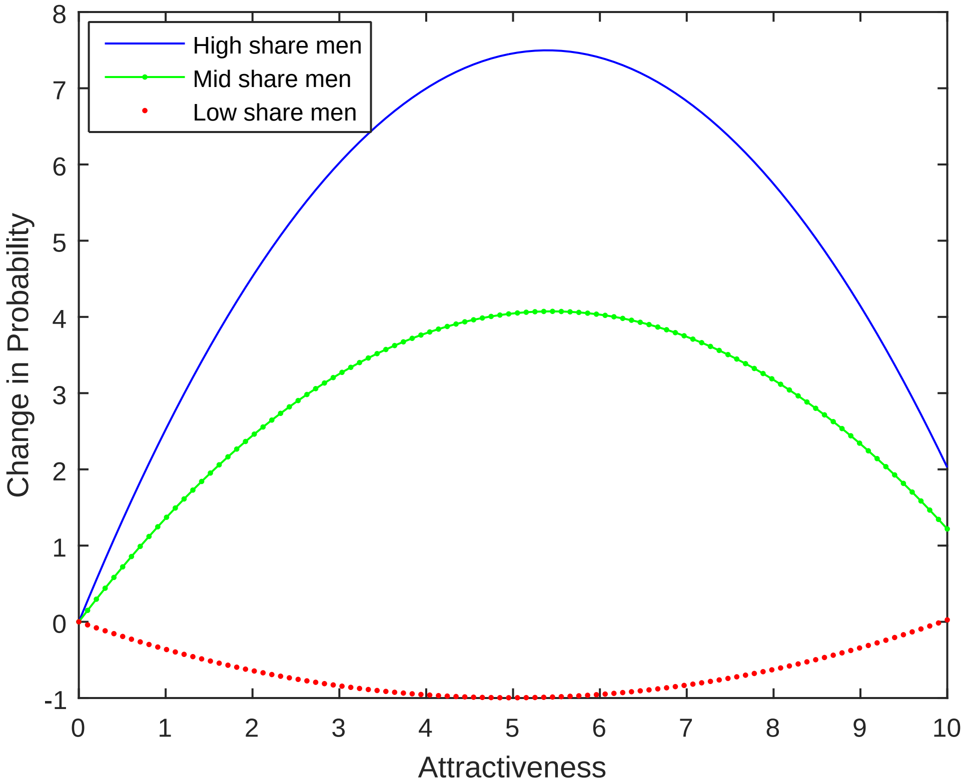


Figure 3: Probability of top 10 job by women's attractiveness, for low mid and high share of men in the field



The high, mean and low shares of men in the field are given by the sample: 0.95, 0.85, 0.72

Table 1: Descriptive statistics: Ph.D graduates in top schools: job placement, publications and share male in field, by gender

	All Graduates			Men Graduates			Women Graduates		
	mean	sd	N	mean	sd	N	mean	sd	N
Rank of Phd inst.	6.54	4.45	752	6.53	4.44	568	6.57	4.51	184
Is first job top 10	0.05	0.22	752	0.04	0.21	568	0.07	0.25	184
Rank of first job	20.57	22.61	291	20.03	21.97	208	21.94	24.23	83
Rank of job in year 7	22.58	23.64	253	22.21	23.46	187	23.62	24.29	66
Hc index in year 7	6.87	4.44	451	7.11	4.63	332	6.19	3.83	119
Share male in field at graduation	0.85	0.07	751	0.86	0.07	567	0.85	0.07	184

Table 2: Distribution of PhD graduates across economic fields, by gender

	All Graduates		Men Graduates		Women Graduates	
	mean	sd	mean	sd	mean	sd
Econometrics	0.04	0.20	0.04	0.20	0.04	0.19
Micro/Theory	0.21	0.41	0.23	0.42	0.16	0.37
Macro	0.10	0.30	0.10	0.31	0.09	0.29
International	0.08	0.27	0.08	0.27	0.08	0.27
Public	0.04	0.21	0.04	0.20	0.05	0.22
Labor	0.13	0.34	0.13	0.33	0.15	0.36
IO	0.07	0.25	0.06	0.23	0.10	0.30
Devel/Growth	0.07	0.26	0.07	0.25	0.09	0.28
Finance	0.11	0.32	0.12	0.33	0.08	0.27
Other	0.14	0.35	0.13	0.34	0.16	0.37
N	751		567		184	

Table 3: Descriptive Statistics: Raters

	mean	sd	min	max
Female	0.52	0.50	0	1
Age	33.26	10.89	18	71
Years of education	15.22	2.44	9	20
Photographs rated	50.71	59.75	1	905
N	241			

Table 4: Appearance ratings of Ph.D graduates in top schools, by gender

	All Graduates		Men Graduates		Women Graduates		Men-Women
	mean	sd	mean	sd	mean	sd	difference in means
Attractive	4.60	1.21	4.36	1.09	5.33	1.27	-0.96***
S.D. of attractive rating	2.06	0.44	2.11	0.43	1.91	0.43	0.20***
Attractive by female raters	4.49	1.43	4.24	1.34	5.24	1.46	-0.99***
S.D. of attractive by female	2.07	0.64	2.13	0.63	1.88	0.62	0.25***
Attractive by male raters	4.71	1.32	4.48	1.22	5.42	1.36	-0.94***
S.D. of attractive by male	1.90	0.67	1.93	0.68	1.81	0.63	0.16**
Intelligent	6.70	0.74	6.68	0.76	6.78	0.67	-0.11**
S.D of intelligent rating	1.61	0.39	1.64	0.39	1.52	0.35	0.12***
Intelligent by female raters	6.80	0.90	6.76	0.91	6.91	0.83	-0.14**
S.D. of intelligent by female	1.55	0.53	1.60	0.53	1.39	0.51	0.21***
Intelligent by male raters	6.62	0.91	6.60	0.93	6.67	0.88	-0.07
S.D. of intelligent by male	1.55	0.62	1.57	0.62	1.50	0.59	0.06*
N	752		568		184		

Last column reports difference in means, with t-test, where * Denotes significance at 10%; ** Denotes significance at 5%; *** Denotes significance at 1%

Table 5: OLS regression models predicting the hc-index of publications

	hc index 7 years after graduation						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Woman	1.495	1.344	-0.951	-1.120	0.192	-0.529	-2.046
	(2.139)	(2.079)	(2.647)	(2.620)	(2.584)	(1.687)	(3.710)
Attractive	0.731***	0.737***	0.880***	0.966***	0.968***	0.504***	0.508***
	(0.220)	(0.214)	(0.292)	(0.290)	(0.288)	(0.190)	(0.190)
Woman X Attractive	-0.592	-0.566	-0.184	-0.138	-0.433	-0.045	-0.124
	(0.406)	(0.394)	(0.510)	(0.505)	(0.498)	(0.326)	(0.339)
Rank of PhD inst.		-0.245***	-0.264***	-0.276***	-0.249***	-0.081**	-0.081**
		(0.047)	(0.060)	(0.059)	(0.060)	(0.040)	(0.040)
Rank of first job			-0.045***	-0.042***	-0.041***	-0.017**	-0.017**
			(0.011)	(0.011)	(0.011)	(0.007)	(0.008)
Graduated in 2003				-1.011	-1.117	-0.855	-0.845
				(0.871)	(0.871)	(0.569)	(0.570)
Graduated in 2004				-1.067	-1.155	-0.611	-0.621
				(0.878)	(0.890)	(0.582)	(0.584)
Graduated in 2005				-1.089	-1.433*	-0.576	-0.602
				(0.848)	(0.854)	(0.560)	(0.562)
Graduated in 2006				-2.657***	-2.878***	-1.425**	-1.418**
				(0.863)	(0.885)	(0.584)	(0.585)
Publication in year 7						0.156***	0.155***
						(0.009)	(0.009)
Intelligent							0.161
							(0.274)
Woman X Intelligent							0.280
							(0.551)
Field fixed effect					Y	Y	Y
Constant	3.938***	5.410***	6.765***	7.580***	7.803***	1.630	0.564
	(0.985)	(0.997)	(1.425)	(1.524)	(1.900)	(1.291)	(2.273)
N	451	451	239	239	239	239	239
Adjusted R^2	0.026	0.080	0.191	0.213	0.254	0.682	0.681

* Denotes significance at 10%; ** Denotes significance at 5%; *** Denotes significance at 1%

Table 6: Logit regression models predicting first job in top 10 school

	(1)	(2)	(3)	(4)
Woman	-0.976	-1.074*	-0.734	-1.075
	(0.617)	(0.650)	(1.647)	(1.697)
Attractive	0.025	0.019		0.018
	(0.057)	(0.057)		(0.058)
Attractive^2	-0.002	-0.001		-0.001
	(0.006)	(0.006)		(0.006)
Woman X Attractive	0.376*	0.416*		0.405*
	(0.229)	(0.241)		(0.243)
Woman X Attractive^2	-0.035*	-0.039*		-0.038*
	(0.021)	(0.022)		(0.022)
Intelligent			0.162	0.145
			(0.194)	(0.191)
Woman X Intelligent			0.230	0.008
			(0.492)	(0.494)
Intelligent^2			-0.012	-0.011
			(0.014)	(0.014)
Woman X Intelligent^2			-0.017	-0.000
			(0.037)	(0.037)
Rank of PhD inst.		-0.004**	-0.004**	-0.004**
		(0.002)	(0.002)	(0.002)
Micro/Theory		-0.019	-0.009	-0.018
		(0.037)	(0.037)	(0.037)
Macro		-0.017	-0.010	-0.017
		(0.041)	(0.041)	(0.041)
International		0.001	0.013	0.001
		(0.040)	(0.040)	(0.040)
Public		-0.058	-0.036	-0.056
		(0.058)	(0.057)	(0.058)
Labor		0.005	0.012	0.006
		(0.037)	(0.037)	(0.037)
IO		-0.071	-0.057	-0.068
		(0.057)	(0.057)	(0.057)
Devel/Growth		-0.014	-0.005	-0.014
		(0.041)	(0.041)	(0.041)
Finance		-0.089	-0.085	-0.089
		(0.057)	(0.057)	(0.057)
Other		-0.103*	-0.094	-0.103*
		(0.057)	(0.058)	(0.057)
Year graduated FE		Y	Y	Y
N	752	751	751	751
Pseudo R^2	0.034	0.118	0.094	0.121

Marginal effects are reported. * Denotes significance at 10%; ** Denotes significance at 5%; *** Denotes significance at 1%

Table 7: Logit regression models predicting first job in top 10 school, with share males in field interactions

	(1)	(2)	(3)	(4)	(5)
Woman	29.896**	28.366**	29.258**	14.682	39.962
	(13.497)	(13.011)	(13.488)	(25.750)	(26.698)
Attractive	1.358	1.279	1.126		1.197
	(0.943)	(0.950)	(0.922)		(0.937)
Attractive^2	-0.153	-0.142	-0.124		-0.128
	(0.103)	(0.103)	(0.100)		(0.101)
Woman X Attractive	-11.368**	-10.764**	-11.052**		-10.716**
	(4.962)	(4.782)	(4.938)		(5.015)
Woman X Attractive^2	1.078**	1.019**	1.041**		1.007**
	(0.456)	(0.440)	(0.452)		(0.458)
Share men in field	3.209	3.049	2.694	-17.892	-14.799
	(2.378)	(2.408)	(2.340)	(11.020)	(10.852)
Attractive X Sh men	-1.521	-1.422	-1.245		-1.328
	(1.053)	(1.060)	(1.031)		(1.050)
Attractive^2 X Sh men	0.172	0.159	0.138		0.143
	(0.114)	(0.115)	(0.112)		(0.113)
Woman X Sh men	-39.736**	-37.771**	-38.894**	-19.807	-53.124
	(18.015)	(17.364)	(17.940)	(32.798)	(34.343)
Attractive X W X Sh men	15.079**	14.308**	14.675**		14.267**
	(6.617)	(6.376)	(6.563)		(6.653)
Attractive^2 X W X Sh men	-1.426**	-1.350**	-1.379**		-1.337**
	(0.608)	(0.586)	(0.601)		(0.607)
Intelligent				-4.458*	-4.471*
				(2.710)	(2.644)
Intelligent^2				0.340*	0.342*
				(0.204)	(0.199)
Woman X Intelligent				-4.311	-3.291
				(7.714)	(7.050)
Woman X Intelligent^2				0.319	0.234
				(0.576)	(0.527)
Intelligent X Sh men				5.520*	5.485*
				(3.335)	(3.242)
Intelligent^2 X Sh men				-0.420*	-0.419*
				(0.251)	(0.244)
Intelligent X W X Sh men				5.842	4.361
				(9.815)	(8.900)
Intelligent^2 X W X Sh				-0.433	-0.311
				(0.732)	(0.665)
Rank of PhD inst.		-0.003*	-0.003*	-0.004*	-0.003*
		(0.002)	(0.002)	(0.002)	(0.002)
Year graduated FE			Y	Y	Y
N	751	751	751	751	751
Pseudo R^2	0.074	0.085	0.100	0.061	0.122

Marginal effects are reported. * Denotes significance at 10%; ** Denotes significance at 5%; *** Denotes significance at 1%

A Appendix

Table A.1: Robustness: using different attractiveness measures in OLS regression models predicting the hc-index of publications

	Raters						Ratings	
	All		Women		Men			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Reliable		Reliable		Reliable	Rescaled	Normalized
Woman	0.192	0.164	-0.412	-0.408	-0.843	-0.588	-1.475	-1.845***
	(2.584)	(2.385)	(2.168)	(2.144)	(2.419)	(2.145)	(2.154)	(0.633)
Attractive	0.968***	0.929***	0.717***	0.718***	0.704***	0.705***	5.320***	1.738***
	(0.288)	(0.278)	(0.234)	(0.232)	(0.256)	(0.247)	(1.890)	(0.559)
Woman X Attractive	-0.433	-0.439	-0.304	-0.306	-0.185	-0.254	-0.728	-0.520
	(0.498)	(0.464)	(0.422)	(0.418)	(0.453)	(0.407)	(3.637)	(0.986)
Rank of PhD inst.	-0.249***	-0.250***	-0.241***	-0.239***	-0.254***	-0.257***	-0.255***	-0.256***
	(0.060)	(0.060)	(0.060)	(0.059)	(0.060)	(0.060)	(0.060)	(0.060)
Rank of first job	-0.041***	-0.042***	-0.043***	-0.043***	-0.041***	-0.042***	-0.042***	-0.042***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Constant	7.803***	8.157***	9.086***	9.138***	8.538***	8.759***	9.810***	12.488***
	(1.900)	(1.842)	(1.741)	(1.728)	(1.904)	(1.840)	(1.669)	(1.549)
N	239	239	239	239	238	237	239	239
Adjusted R^2	0.254	0.254	0.248	0.248	0.243	0.246	0.245	0.250

All regressions include year of graduation and field fixed effects. * Denotes significance at 10%; ** Denotes significance at 5%; *** Denotes significance at 1%

(A3)

Table A.2: Robustness: using different attractiveness measures in Logit regression models predicting first job in top 10 school

	Raters						Ratings	
	All		Women		Men			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Reliable		Reliable		Reliable	Rescaled	Normalized
Woman	-1.074*	-0.916	-0.601	-0.599	-0.343	-0.340	-0.628*	0.041*
	(0.650)	(0.566)	(0.421)	(0.420)	(0.368)	(0.344)	(0.364)	(0.024)
Attractive	0.019	0.023	0.036	0.036	0.031	0.028	-0.157	0.016
	(0.057)	(0.055)	(0.043)	(0.043)	(0.051)	(0.047)	(0.278)	(0.016)
Attractive^2	-0.001	-0.002	-0.003	-0.003	-0.003	-0.002	0.214	0.016
	(0.006)	(0.006)	(0.005)	(0.004)	(0.005)	(0.005)	(0.268)	(0.021)
Woman X Attractive	0.416*	0.359*	0.246	0.245	0.135	0.133	2.412*	0.080
	(0.241)	(0.212)	(0.161)	(0.160)	(0.137)	(0.130)	(1.244)	(0.067)
Woman X Attractive^2	-0.039*	-0.034*	-0.023	-0.023	-0.012	-0.012	-2.129**	-0.152**
	(0.022)	(0.020)	(0.015)	(0.015)	(0.013)	(0.012)	(1.044)	(0.077)
Rank of PhD inst.	-0.004**	-0.004**	-0.004**	-0.004**	-0.004**	-0.004**	-0.004**	-0.004**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
N	751	751	751	751	749	748	751	751
Pseudo R^2	0.118	0.117	0.118	0.118	0.100	0.102	0.117	0.117

All regressions include year of graduation and field fixed effects. * Denotes significance at 10%; ** Denotes significance at 5%; *** Denotes significance at 1%

Table A.3: Robustness: using different attractiveness measures in Logit regression models predicting first job in top 10 school

	Raters						Ratings	
	All		Women		Men			
	(1)	(2) Reliable	(3)	(4) Reliable	(5)	(6) Reliable	(7) Rescaled	(8) Normalized
Woman	29.258**	28.242**	19.132**	19.072**	-0.848	2.685	10.421	0.042
	(13.488)	(11.975)	(9.714)	(9.591)	(4.811)	(4.643)	(6.558)	(0.309)
Attractive	1.126	0.986	0.532	0.541	-0.044	0.148	4.147	-0.072
	(0.922)	(0.863)	(0.610)	(0.603)	(0.603)	(0.610)	(4.046)	(0.222)
Attractive^2	-0.124	-0.110	-0.056	-0.057	-0.002	-0.023	-4.399	-0.125
	(0.100)	(0.095)	(0.066)	(0.065)	(0.063)	(0.066)	(4.028)	(0.267)
Woman X Attractive	-11.052**	-10.794**	-7.176**	-7.165**	0.278	-1.122	-36.411*	0.400
	(4.938)	(4.457)	(3.595)	(3.554)	(1.787)	(1.750)	(21.837)	(0.563)
Woman X Attractive^2	1.041**	1.027**	0.669**	0.669**	-0.014	0.119	31.478*	0.000
	(0.452)	(0.415)	(0.332)	(0.329)	(0.164)	(0.163)	(18.077)	(.)
Share men in field	2.694	2.297	1.235	1.260	-0.395	0.120	1.008	-0.030
	(2.340)	(2.165)	(1.563)	(1.540)	(1.642)	(1.598)	(1.094)	(0.170)
Attractive X Sh men	-1.245	-1.084	-0.559	-0.569	0.097	-0.127	-4.840	0.102
	(1.031)	(0.968)	(0.691)	(0.684)	(0.704)	(0.702)	(4.556)	(0.253)
Attractive^2 X Sh men	0.138	0.122	0.060	0.061	-0.001	0.022	5.200	0.159
	(0.112)	(0.106)	(0.074)	(0.074)	(0.074)	(0.075)	(4.535)	(0.304)
Woman X Sh men	-38.894**	-37.452**	-25.341*	-25.264**	0.543	-3.731	-13.885	-0.005
	(17.940)	(15.936)	(12.933)	(12.765)	(5.762)	(5.721)	(8.513)	(0.366)
Attractive X W X Sh men	14.675**	14.297**	9.503**	9.489**	-0.149	1.544	48.583*	-0.362
	(6.563)	(5.926)	(4.776)	(4.721)	(2.142)	(2.156)	(28.299)	(0.658)
Attractive^2 X W X Sh men	-1.379**	-1.357**	-0.884**	-0.884**	0.000	-0.161	-41.893*	-0.187*
	(0.601)	(0.551)	(0.441)	(0.436)	(0.196)	(0.201)	(23.384)	(0.103)
Rank of PhD inst.	-0.003*	-0.003*	-0.003*	-0.003*	-0.004*	-0.004*	-0.004*	-0.004*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
N	751	751	751	751	749	748	751	751
Pseudo R^2	0.100	0.103	0.089	0.090	0.053	0.057	0.083	0.069

All regressions include year of graduation and field fixed effects. * Denotes significance at 10%; ** Denotes significance at 5%; *** Denotes significance at 1%