Discrimination

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1 Introduction

Example 1:

Imagine two tables in a restaurant. The bills of the two tables got mixed up and you don't know which bill belongs to each table. One of the bills is was for $40 and one was $30. Here is what else you know.

Table 1	Table 2
Two men, early 20s	Two men, early 20s
Wearing Business Suits	Wearing Jeans and UCSD T-shirts
Left a cash tip of $6	Left cash tip of $6

Which table had the $40 tab, and which had the $30 tab?

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Which table had the $40 tab, and which had the $30 tab?

- Your answer depends on which you think is more likely, the people in suits spend more on lunch or whether they give bigger tips, that is, which is bigger, Pr(20% tip| suits) or Pr($40 lunch| suits).
- Your answer might depend on your personal experience as a waiter/waitress.

Example 2:

Suppose the waitperson at the restaurant says, “These were my tables, and I know the people in UCSD T-shirts left the 15% tip and the people in suits left the 20% tip. I knew that the UCSD-T-Shirt-wearers would leave a lousy tip when they walked in and this just proves it."
Should you agree with this statement? See anything to make you suspicious?

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- If you were to test the hypothesis that USCD-T-Shirts imply bad tippers, how would you design this test?
- Did the waitperson conduct such a test?

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- If you were to test the hypothesis that USCD-T-Shirts imply bad tippers, how would you design this test?
- Did the waitperson conduct such a test? Maybe not
- If the belief was that suits leave bigger tips than T-shirts, maybe the waitperson gave better service to the suits.
  - As a result, she got a lower tip from the T-shirts.
  - But it was a "self-fulfilling-expectations"

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  - As a result, she got a lower tip from the T-shirts.
  - But it was a "self-fulfilling-expectation"
- This can generate a bad cycle:
  - Low expected tip $\Rightarrow$ bad service $\Rightarrow$ Low tips $\Rightarrow$ low expected tip $\Rightarrow$ bad service ....etc.
- It can be impossible even for great tipper to get good service in a T-shirt!

Example 3:

This example is less silly and more serious. Suppose an employer interviews two people for a job. Both look identical on paper and both made an equally good impression in the interview. How does the employer break the tie?

The only difference is that one is from ethnic group Γ that the employer has a lot of experience with and has had many good employees from that group. The other is from a group Ω you have only a little experience with, and that experience was bad. In fact, there are generally more from Γ among successful employees than from Ω . Is the employer justified in using ethnicity to break the tie?

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- In statistical terms, before accounting for ethnicity $\Pr($success$|$ job test) was the same for both candidates.
- But, the base rate is that Γs are more successful when hired.
- Using Bayes rule to update $\Pr($success$|$ job test), then $\Pr($success$|$ Γ,job test$) > \Pr($success$|$ Ω,job test).
- It is logical to use statistics as a basis for discrimination. Why not use ethnicity *if it is legitimately correlated with job performance?*
- This is like our model of information cascades last time: if your prior (the base rate) on Γs is that they are more likely to succeed than Ωs, then if they each get identical scores on a job test (a result which contradicts your priors) it may not be enough information to cause you to reverse your ranking from the prior.

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Statistical Discrimination

- Such discrimination is called *Statistical Discrimination.*
- We give it this name because it follows from a dispassionate application of Bayes' rule.
- It is not motivated by any stereotype or malice or favoritism.
- In fact, statistical discrimination is based on facts and is purely rational choice.
- Here's an example:
  - Two job candidates both have 4.0 GPAs
  - One is from UCSD and one from Stanford.
  - We know Stanford always gives easy As to everyone.
  - So good grades from UCSD is more meaningful.
  - No one would blame an employer of always favoring the UCSD candidate if the two otherwise looked the same.
- So, statistical discrimination isn't harmful or inefficient, right?

Statistical Discrimination

- So, statistical discrimination isn't harmful or inefficient, right?
- That depends....
- Has the base rate (group Γ is more successful than group Ω in the economy in general) been established with a clean experiment? What would that mean?

Statistical Discrimination

- So, statistical discrimination isn't harmful or inefficient, right?
- That depends....
- Has the base rate (group Γ is more successful than group Ω in the economy in general) been established with a clean experiment? What would that mean?
- This means that both groups Γ and Ω were given equal chances to succeed
  - that is, there was random assignment to conditions.
- This means both faced the same expectations when evaluated.
  - This means the experiment was "double-blind" and the experimenter didn't know who was assigned to what conditions.
- With ethnic groups in society, neither of these has been met.
- What about self-fulfilling expectations?

Statistical Discrimination

- What about self-fulfilling expectations?
- Suppose, as the example of the employer above, he expects the Γs to be more productive.
- Productivity, in turn, depends on investment in skills.
- Since Ωs know that if they are tied with (or even a little better than) Γs on any job interview, they won't get the job anyway, then they have less incentive to invest in skills. By the same token, Γs have more incentive to invest in skills.
- Because of their greate investment in skills, it follows that, in the overall population, the Γs will have a greater chance at being successful than the Ωs.
- This means the base rate may be both the *result of* and the *reason for* discrimination.
- Note that none of it *needs* to be malicious, but the beliefs become self-sustaining and, as such, there may be too much investment in skills in Γ and too little investment in Ω (relative to an economy-wide efficiency standard).
- So even statistical discrimination can lead to economically inefficient outcomes.

Statistical Discrimination

- What can society do to counteract statistical discrimination?

Statistical Discrimination

- What can society do to counteract statistical discrimination?
- Needs to encourage more investment in skills by the Ωs.
  - Lower educational costs.
  - Promote hiring
  - Prevent malicious discrimination
- Problem is that if this "affirmative action" isn't done correctly, it can itself alter expectations in a way that will undermine its objectives.
- See these:
  - Stephen Coate and Glenn C. Loury, "Will Affirmative-Action Policies Eliminate Negative Stereotypes?" *American Economic Review*, 1993.
  - Glenn C. Loury, *The Anatomy of Racial Inequality* (The W. E. B. Du Bois Lectures), Harvard University Press, 2002

2 Testing Discrimination

Statistical discrimination and self-fulfilling expectations make it hard to uncover discrimination with data from surveys on wages and hiring. This means controlled experiments could be more informative. There are three types of studies.

Lab Studies

- Create "status" in the lab
- Study race or gender under controlled settings

Field Studies

- Keep track of characteristics when assigning jobs.
- Nobody needs to know you'll be studying discrimination.

Audit Studies

- Real experiments where people try to control characteristics other than race.
- Targets of study don't know their in an experiment.

Lab Studies

S Ball, C Eckel, PJ Grossman, W Zame , "Status in Markets, Quarterly Journal of Economics, 2001

- Hypothesis: People with higher "status" will get better deals in markets.
- Choose a standard market experiment where demand and supply go up in "steps"
- The artificially generate status
  - Give subjects a "trivia" quiz, with impossible questions
  - Choose "sellers" or "buyers" (two different conditions) to those who "performed better"
  - The criteria for "better" was uncorrelated with correctness, but subjects didn’t know this.
  - Gave status with small ceremony, stars on collars, applause.

QUIZ

1. What percentage of the U. S. Federal budget is allocated to national defense? _____ .
2. What was the rate of inflation in the U. S. in 1990? _____ .
3. What percentage of the homeless in the U. S. are adult males? _____ .
4. What percentage of autos sold in the U. S. are imported from Germany? _____ .
5. What percentage of immigrants to the U. S. are illegal? _____ .

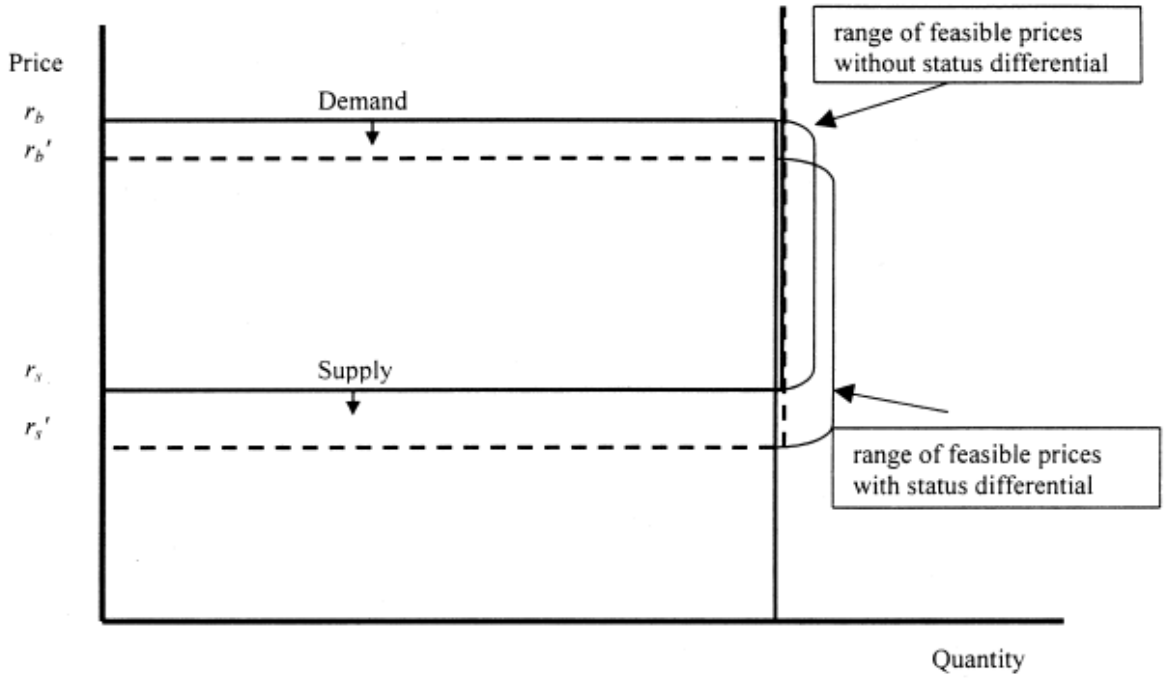

FIGURE I
Supply and Demand in a Box Design Market: Buyer Status > Seller Status

Results

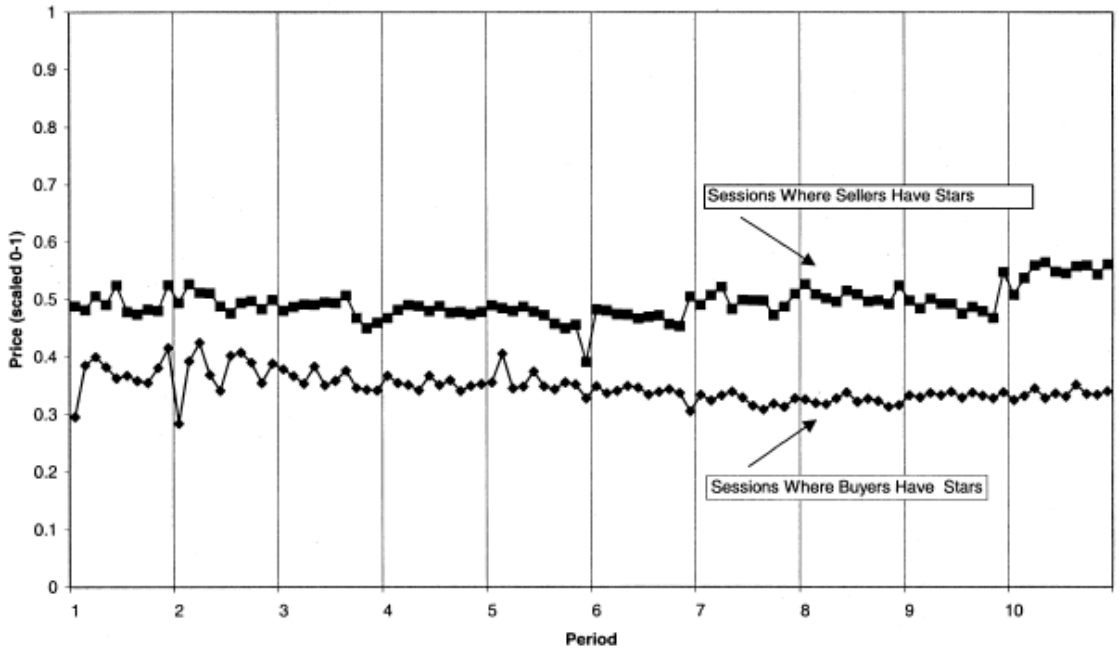

FIGURE II
Average Prices for Buyer Status and Seller Status Sessions

- Note that better prices go to the side with more status, regardless of whether it is demand or supply.
- Follow up questions reveal that having a star was perceived as being more aggressive and more deserving and more desirable.
- The point here is that it was trivially easy to generate status and entitlement, and that these can lead to significantly different outcomes.

Audit Study

Marianne Bertrand and Sendhil Mullainathan, "Are Emily and Greg More Employable than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination." *American Economic Review,* **94 (4), 2004.**

- There is clear evidence from labor market studies that African Americans earn less and are less likely to be hired than whites.
- How can you test whether employers do actively discriminate, whether statistical or otherwise?
  - Create two people who present themselves equally well and differ only by race.
  - But using "actors" is very difficult to do well because the actors may know what the study is about.
- These researchers use resumes.
  - The objective information on the resumes is the same
  - Names are chosen to sound more likely to be from different ethnic groups.

Design issues:

- Find resumes posted on job search web sites.
- Alter the resume's so that they don't infringe on the rights of the people they take them from, but try to keep everything realistic.
- Get a variety of "quality" of applicants.
  - Chose addresses that were fictitious, from real streets and zip codes.
  - Created 5 random addresses from each zip code in the city.
- Use two cities, Chicago and Boston.
  - Use the same bank of resumes, but switch things to add balance to the design.
- Assign names to resumes
  - Use frequency of names from birth certificates to find names that are relatively good indicators of race.
  - Checked their choices independently with a survey to random people on the street.

- Responded to adds in Boston and Chicago over about 9 month period.
  - Chose adds that only asked for resumes to be emailed, mailed, or faxed in.
- Selected 4 resumes from the bank to send to each add.
  - two high and two low quality.
  - two black and two white names, one of each quality.
- Used male and female names for sales jobs, but used female names for clerical jobs.
- Overall, applied to over 1300 with almost 5000 resumes

Measuring responses

- Measure whether a resume results in a call back or email asking for an interview.

Results:

- Table 1: African-Americans are less likely to receive a call back.

TABLE 1—MEAN CALLBACK RATES BY RACIAL SOUNDINGNESS OF NAMES

	Percent callback for White names	Percent callback for African-American names	Ratio	Percent difference (p-value)
Sample:				
All sent resumes	9.65	6.45	1.50	3.20
	[2,435]	[2,435]		(0.0000)
Chicago	8.06	5.40	1.49	2.66
	[1,352]	[1,352]		(0.0057)
Boston	11.63	7.76	1.50	4.05
	[1,083]	[1,083]		(0.0023)
Females	9.89	6.63	1.49	3.26
	[1,860]	[1,886]		(0.0003)
Females in administrative jobs	10.46	6.55	1.60	3.91
	[1,358]	[1,359]		(0.0003)
Females in sales jobs	8.37	6.83	1.22	1.54
	[502]	[527]		(0.3523)
Males	8.87	5.83	1.52	3.04
	[575]	[549]		(0.0513)

Notes: The table reports, for the entire sample and different subsamples of sent resumes, the callback rates for applicants with a White-sounding name (column 1) an an African-American-sounding name (column 2), as well as the ratio (column 3) and difference (column 4) of these callback rates. In brackets in each cell is the number of resumes sent in that cell. Column 4 also reports the p-value for a test of proportion testing the null hypothesis that the callback rates are equal across racial groups.

- Table 4: The results hold up even when conditioning on quality of the applicants.

TABLE 4—AVERAGE CALLBACK RATES BY RACIAL SOUNDINGNESS OF NAMES AND RESUME QUALITY

	Low	High	Ratio	Difference (p-value)
Panel A: Subjective Measure of Quality (Percent Callback)				
White names	8.50	10.79	1.27	2.29
	[1,212]	[1,223]		(0.0557)
African-American names	6.19	6.70	1.08	0.51
	[1,212]	[1,223]		(0.6084)
Panel B: Predicted Measure of Quality (Percent Callback)				
White names	7.18	13.60	1.89	6.42
	[822]	[816]		(0.0000)
African-American names	5.37	8.60	1.60	3.23
	[819]	[814]		(0.0104)

- Table 5: Resume items that matter are experience, having an email address, having honors.
  - But all these effects matter more for whites than for African-Americans.

TABLE 5—EFFECT OF RESUME CHARACTERISTICS ON LIKELIHOOD OF CALLBACK

Dependent Variable: Callback Dummy Sample:	All resumes	White names	African-American names
Years of experience (*10)	0.07	0.13	0.02
	(0.03)	(0.04)	(0.03)
Years of experience^2 (*100)	−0.02	−0.04	−0.00
	(0.01)	(0.01)	(0.01)
Volunteering? (Y = 1)	−0.01	−0.01	0.01
	(0.01)	(0.01)	(0.01)
Military experience? (Y = 1)	−0.00	0.02	−0.01
	(0.01)	(0.03)	(0.02)
E-mail? (Y = 1)	0.02	0.03	−0.00
	(0.01)	(0.01)	(0.01)
Employment holes? (Y = 1)	0.02	0.03	0.01
	(0.01)	(0.02)	(0.01)
Work in school? (Y = 1)	0.01	0.02	−0.00
	(0.01)	(0.01)	(0.01)
Honors? (Y = 1)	0.05	0.06	0.03
	(0.02)	(0.03)	(0.02)
Computer skills? (Y = 1)	−0.02	−0.04	−0.00
	(0.01)	(0.02)	(0.01)
Special skills? (Y = 1)	0.05	0.06	0.04
	(0.01)	(0.02)	(0.01)
Ho: Resume characteristics effects are all zero (p-value)	54.50 (0.0000)	57.59 (0.0000)	23.85 (0.0080)
Standard deviation of predicted callback	0.047	0.062	0.037
Sample size	4,870	2,435	2,435

Conclusion

- These results point to clear labor market discrimination in inviting applicants for interviews.
- Suggests that simply improving the resumes and skills of poorly performing groups will not be enough to overcome the disadvantage in the market.
- It cannot tell us whether discrimination is statistical discrimination or malicious discrimination.

Field Studies

John A. List, "THE NATURE AND EXTENT OF DISCRIMINATION IN THE MARKETPLACE: EVIDENCE FROM THE FIELD." The Quarterly Journal of Economics, February 2004

- Problem with audit studies is that you cannot separate statistical discrimination (that race/gender may be correlated with real variables) from malicious or "taste-based" discrimination.
- Also, cannot measure how good a bargainer anyone is in, say, housing markets or car markets where audit studies have been conducted.
- He uses a real trading floor of a sports card show.
- He asks volunteers to either buy or sell a card to dealers on the trading floor.
- The dealers do not know it is an experiment.
- He measures what the opening offers

Beauty in the Labor Market

Markus M. Mobius and Tanya S. Rosenblat, "Why Beauty Matters." AER 2006.

- An influential paper by Daniel S. Hamermesh and Jeff E. Biddle in the *AER* (1994) showed that better looking people make more money in the labor market.
  - Later studies showed that better looking professors get higher teacher ratings.
- How can this exist in a competitive market?
- Should profit maximization compete away discrimination?.
  - One possible reason it doesn't is that beauty may actually be productive.
  - Think of movie actors, sales people (or CSI workers?)
- In labor maket studies, however, it is hard to know a person's true productivity.
- Could it be that something unobserved is correlated with beauty that causes beutiful people to be more productive?

- Study this is a laboratory setting.
- This has the advantage of being able to measure productivity.
- They also measure confidence of the "employees" and the expectations of the "employers", which may be key to understanding **why** beauty matters..

Design

- Conducted in Argentina (don’t ask me why).
- Subjects are randomly assigned to be either "employers" or "workers."
- Workers must solve puzzles for 15 minutes.
- Employers set wages based on their forecast of productivity.
  - This will measure biased expectations
- Workers, after solving one practice puzzle forecast their own productivity.
  - This will measure personal confidence.
- Employees and Workers have a brief face-to-face and/or verbal interaction.

Idea of the design

- Beauty works through three chanels:
  - Confidence (attitude of worker)
  - Visual stereotype (viewed)
  - Oral stereotype (spoken)
- By measureing confidence and varyign the amount of visual and oral exposure, they can separate the three effects.
- Psychologists show that beauty is perceived to be correlated with intelligence, social skills, and health (Alan Feingold, 1992; Alice H. Eagly et al., 2001).1
- According to the kernel-of-truth hypothesis, the physical attractiveness stereotype can become a self-fulfilling prophecy:
  - teachers expect better looking kids to outperform in school and devote more attention to children who are perceived to have greater potential (Elaine Hatfield and Susan Sprecher, 1986).
  - Preferential treatment in return builds confidence as well as social and communication skills.

Results:

- The confidence channel operates through workers' beliefs:
  - physically attractive workers are substantially more confident, and worker confidence in return increases wages under oral interaction.
- The two stereotype channels affect employers' beliefs:
  - employers (wrongly) expect good-looking workers to perform better than their less attractive counterparts under both visual and oral interaction, even after controlling for individual worker characteristics and worker confidence.

The Experiment

- Each experimental session includes five workers and five employers who are randomly assigned their roles.
- Employers start with an account of 4,000 points, while workers have no points initially.
- All participants submit their basic labor market characteristics (age, sex, university, matriculation year, previous job experience, extracurricular activities, and hobbies) through an online survey and have their digital photograph taken.
- Workers are asked to solve a practice maze of the lowest level of difficulty and their practice time is recorded. The labor market characteristics of a worker, together with his practice time, becomes his "digital résumé."
- Each worker j is then asked for an estimate C_j of how many mazes of the next level of difficulty he expects to complete during a 15-minute "employment period" at the end of the experiment.
  - This information is kept secret from all other players and provides a measure of worker confidence.
- The worker receives a piece rate of 100 points per solved maze, minus 40 points for each maze that he mispredicted when estimating Cj:

$$(8) \qquad 100 \times A_j - 40 \times |C_j - A_j|.$$

- Each worker is then matched with five different employers.

B: (baseline) Employer B sees only the résumé of the worker.

V: (visual) Employer V sees the résumé and a frontal facial passport-like photograph of the worker.

O: (oral) Employer O sees the résumé and conducts a free-form telephone interview with the worker of up to five minutes in length.

VO: (visual + oral) Employer VO sees the résumé and photograph, and also conducts a telephone conversation of up to five minutes in length.

FTF: (face-to-face) Employer FTF sees the résumé and photograph, and also conducts a face-to-face free-form interview with the worker of up to five minutes in length.[9]

The task of each employer i is to estimate the expected productivity w_{ij} of each worker j in the 15-minute employment period. Employers are provided with the same incentives as workers to reveal truthfully their estimates. Employer i faces a penalty of 40 points for each mispredicted maze of worker j. For example, if employer i decides that worker j can do eight mazes but the worker solves ten, then the employer receives a penalty of 80 points. Therefore, the total compensation Π_i of employer i including the misprediction penalty is:

$$\Pi_i = 4000 - \sum_{j=1}^{5} 40 \times |w_{ij} - A_j|. \tag{9}$$

Each worker j receives five actual wages W_{ij} from the experimenter: one wage for each employer i, which is calculated as follows: with probability 0.8, employer i's estimate is used to pay the worker $W_{ij} = 100w_{ij}$; with probability 0.2, the average estimate $\bar{w}$ of all employers across all workers in the session is used to set the worker's wage to $W_{ij} = 100\bar{w}$ (all draws are i.i.d. across workers and employers).

Results:

Regressions (1) and (2): Beauty doesn't matter for productivity, but confidence (LN PROJECTED) does.

TABLE 3—THE IMPACT OF PRACTICE PERFORMANCE AND BEAUTY ON MAZE SOLVING ABILITY AND CONFIDENCE

	LNACTUAL		LNESTIMATED		
Variable	(1)	(2)	(3)	(4)	(5)
AGE	0.081	0.038	0.181*	0.018	0.018
	(0.065)	(0.064)	(0.074)	(0.060)	(0.060)
AGE * AGE	−0.002†	−0.001	−0.003*	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
MALE	0.331**	0.303**	0.221*	0.015	0.015
	(0.086)	(0.081)	(0.097)	(0.080)	(0.081)
UNIVERSITY2	−0.113	−0.088	−0.026	0.035	0.036
	(0.143)	(0.139)	(0.163)	(0.127)	(0.128)
UNIVERSITY3	0.042	0.115	−0.358	−0.183	−0.184
	(0.201)	(0.197)	(0.229)	(0.179)	(0.180)
INTERNET	0.158†	0.136†	0.089	0.042	0.042
	(0.083)	(0.080)	(0.094)	(0.074)	(0.075)
TEAMSPORT	0.062	0.054	0.133	0.127	0.128
	(0.088)	(0.085)	(0.101)	(0.078)	(0.079)
PREVJOBS	0.057	0.052	0.012	−0.003	−0.003
	(0.037)	(0.036)	(0.042)	(0.033)	(0.033)
LNACTUAL				0.177*	0.177*
				(0.078)	(0.079)
LNPROJECTED		0.160**		0.429**	0.429**
		(0.054)		(0.051)	(0.051)
BEAUTY	−0.034		0.162**	0.135**	0.133**
	(0.042)		(0.048)	(0.038)	(0.051)
BEAUTY * MALE					0.002
					(0.075)
N	163	163	163	163	163
R^2	0.323	0.362	0.304	0.587	0.587

Significance levels: †: 10 percent; *: 5 percent; **: 1 percent. The dependent variable is LNACTUAL in columns (1) and (2) and LNESTIMATED in columns (3), (4), and (5); standard errors are shown in parentheses. The base university is UNIVERSITY1. All regressions include the following additional resume controls: choice of college major, hobby variables, and previous job market experience.

In the Baseline condition, without contact, Beauty doesn't matter, but confidence does. Both beauty and confidence matter in other treatments.

TABLE 4—GROSS AND DECOMPOSED BEAUTY PREMIA IN TREATMENTS (B) TO (FTF)

	Gross beauty premia				
Variable	(B)	(V)	(O)	(VO)	(FTF)
AGE	0.009	0.007	−0.014	0.088*	−0.121*
	(0.047)	(0.042)	(0.038)	(0.040)	(0.048)
AGE * AGE	0.000	0.000	0.000	−0.002*	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
MALE	0.050	0.069	0.130*	0.180**	0.083
	(0.071)	(0.064)	(0.057)	(0.059)	(0.071)
LNPROJECTED	0.403**	0.397**	0.407**	0.375**	0.372**
	(0.043)	(0.038)	(0.035)	(0.036)	(0.043)
LNACTUAL	−0.038	0.010	−0.014	0.095†	−0.017
	(0.063)	(0.057)	(0.051)	(0.056)	(0.064)
BEAUTY	0.017	0.131**	0.129**	0.124**	0.167**
	(0.040)	(0.042)	(0.034)	(0.036)	(0.043)
SETWAGE	−0.010	−0.072	0.098*	−0.046	0.033
	(0.055)	(0.052)	(0.046)	(0.048)	(0.057)
SETWAGE * BEAUTY	−0.058	−0.099†	0.005	0.022	−0.044
	(0.057)	(0.053)	(0.048)	(0.050)	(0.058)
N	163	161	163	162	163
R^2	0.61	0.696	0.751	0.776	0.605

	Decomposed beauty premia with worker confidence				
Variable	(B)	(V)	(O)	(VO)	(FTF)
AGE	0.011	−0.002	−0.023	0.081*	−0.138**
	(0.048)	(0.043)	(0.036)	(0.039)	(0.046)
AGE * AGE	0.000	0.000	0.000	−0.001*	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
MALE	0.052	0.054	0.120*	0.173**	0.085
	(0.071)	(0.066)	(0.053)	(0.057)	(0.068)
LNPROJECTED	0.414**	0.386**	0.322**	0.302**	0.298**
	(0.053)	(0.046)	(0.039)	(0.044)	(0.050)
LNACTUAL	−0.033	0.014	−0.049	0.064	−0.046
	(0.065)	(0.059)	(0.050)	(0.055)	(0.062)
BEAUTY	0.018	0.114*	0.087*	0.098**	0.121**
	(0.042)	(0.045)	(0.034)	(0.037)	(0.043)
SETWAGE	0.052	0.106	0.059	−0.023	0.555**
	(0.207)	(0.206)	(0.151)	(0.176)	(0.207)
SETWAGE * BEAUTY	−0.053	−0.088	0.022	0.013	0.002
	(0.058)	(0.055)	(0.046)	(0.051)	(0.058)
LNESTIMATED	−0.004	0.100	0.205**	0.186**	0.328**
	(0.098)	(0.094)	(0.064)	(0.068)	(0.097)
SETWAGE * LNESTIMATED	−0.034	−0.094	0.025	−0.009	−0.282**
	(0.110)	(0.108)	(0.078)	(0.091)	(0.107)
N	163	161	163	162	163
R^2	0.611	0.700	0.783	0.796	0.647

Conclusion

There is a belief the beautiful people are more productive, and this is reinforced by a more confident attitude by the beautiful people.