Econ 211

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Discrimination

Two Types of Discrimination

- Taste-based discrimination
  - A pure disutility for hiring, working with, or being around a certain group
  - No economic motive
  - Example?
- Statistical discrimination
  - Membership in a certain group can be correlated with other characteristics that are relevant for hiring, eg education level
  - Given this correlation, it may make sense for hiring manager to use group membership as a criteria
  - Purely economic motivation, no actual animus towards group
  - Example?

Are Emily and Greg More Employable Than Lakisha and Jamal?

- Want to examine racial discrimination in job hiring practices
- Normally race and job-relevant characteristics (education, skills, etc) may be correlated
- Need an experimental design where race is truly randomly assigned
- Research design by Bertrand and Mullainathan (2004):
  - Create many composite resumes based on real ones
  - Some are high skill, some are low skill
  - Randomly put either white-sounding or African-American-sounding name on top of each resume
  - Send resumes to real hiring managers in response to 1300 real ads
  - Send 4 resumes (1 of each type) to each
  - Measure percentage of callbacks each resume gets

Names Used Were Distinctly Black or White

TABLE A1—FIRST NAMES USED IN EXPERIMENT

White female Name	L(W)/L(B)	Perception White	African-American female Name	L(B)/L(W)	Perception Black
Allison	∞	0.926	Aisha	209	0.97
Anne	∞	0.962	Ebony	∞	0.9
Carrie	∞	0.923	Keisha	116	0.93
Emily	∞	0.925	Kenya	∞	0.967
Jill	∞	0.889	Lakisha	∞	0.967
Laurie	∞	0.963	Latonya	∞	1
Kristen	∞	0.963	Latoya	∞	1
Meredith	∞	0.926	Tamika	284	1
Sarah	∞	0.852	Tanisha	∞	1
Fraction of all births:			Fraction of all births:		
3.8 percent			7.1 percent		
White male Name	L(W)/L(B)	Perception White	African-American male Name	L(B)/L(W)	Perception Black
Brad	∞	1	Darnell	∞	0.967
Brendan	∞	0.667	Hakim		0.933
Geoffrey	∞	0.731	Jamal	257	0.967
Greg	∞	1	Jermaine	90.5	1
Brett	∞	0.923	Kareem	∞	0.967
Jay	∞	0.926	Leroy	44.5	0.933
Matthew	∞	0.888	Rasheed	∞	0.931
Neil	∞	0.654	Tremayne	∞	0.897
Todd	∞	0.926	Tyrone	62.5	0.900
Fraction of all births:			Fraction of all births:		
1.7 percent			3.1 percent		

Evidence for Discrimination

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)

- Summary?

Effect of Resume Characteristics

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

- Summary?

Gender

Motivation

- So far we have focused in this class mostly on behavior of an entire population
- However, lots of evidence in economics of *individual differences* in race, gender, age, etc
- Gender is correlated with different risk preferences and social preferences, for example
- Gender especially easy to study because it is randomly assigned

Eckel and Grossman (2002)

- Subjects choose one of five risky options
  - Option 1 is lowest risk and lowest expected payoff
  - Option 5 is highest risk and highest expected payoff
- Two framings
  - Loss frame: paid $6 for completing experiment
  - Gain frame: no fixed payment

Table 1
Gamble choices, expected payoffs, and risk in the two alternative framings

			Payoff		Expected payoff		
Gamble choice	Event	Probability (%)	Loss framing ($)	No-Loss framing ($)	Loss framing ($)	No-Loss framing ($)	Risk
1	A	50	10	16	10	16	0.00
	B	50	10	16			
2	A	50	18	24	12	18	4.24
	B	50	6	12			
3	A	50	26	32	14	20	8.48
	B	50	2	8			
4	A	50	34	40	16	22	12.73
	B	50	−2	4			
5	A	50	42	48	18	24	16.97
	B	50	−6	0			

The level of risk is represented as the S.D. of expected payoff.

Men's Choices vs Women's Choices

Table 2
Frequency distributions of gamble choices in relation to the subject's sex and the framing treatment

	All subjects		Men		Women	
Gamble choice	Loss framing	No-Loss framing	Loss framing	No-Loss framing	Loss framing	No-Loss framing
1	7	3	2	0	5	3
2	25	10	11	6	14	4
3	48	17	15	10	33	7
4	32	9	18	6	14	3
5	36	13	26	10	10	3
Total	148	52	72	32	76	20
Mean gamble choice (S.D.)	3.44 (1.17)	3.37 (1.22)	3.76 (1.18)	3.63 (1.13)	3.14 (1.08)	2.95 (1.28)

- Summary of these results?
- Question: can we say this is due entirely to biology?

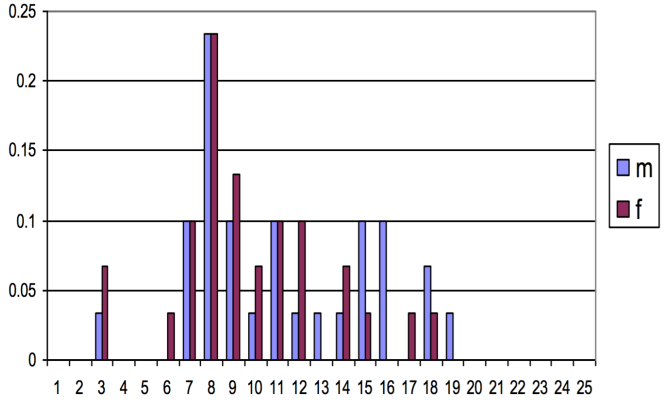
More Motivation

- We see employment differences between men and women in many dimensions
  - Wages
  - Choice of job
  - Choice to work at all
- What causes these differences?

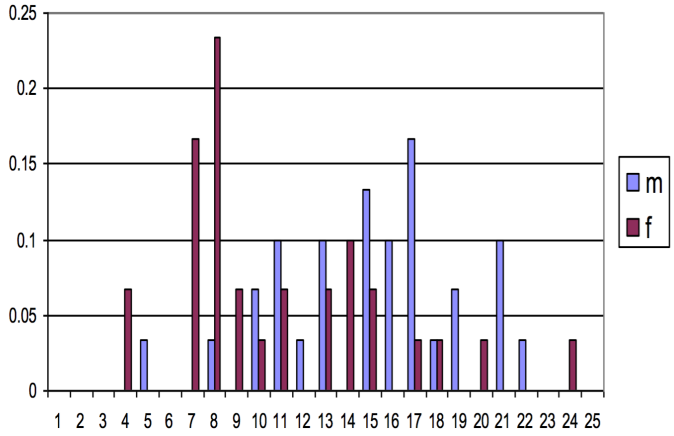
Gender Differences in Competition

- Research design by Gneezy, Niederle, and Rustichini (2003)
  - Undergraduate engineering students
  - Groups of 6 students (3 men, 3 women)
  - Task: solving mazes of varying difficulty on the computer
- Two treatments:
  1. Non-competitive (piece rate):
     - Paid $2 for every solved maze
     - Score is private
  2. Competitive (tournament):
     - Person that solves most mazes in group gets $12 for each maze solved
     - All others in group receive nothing
     - Winner anonymous

Performance by Gender in Piece Rate



Performance by Gender in Tournament



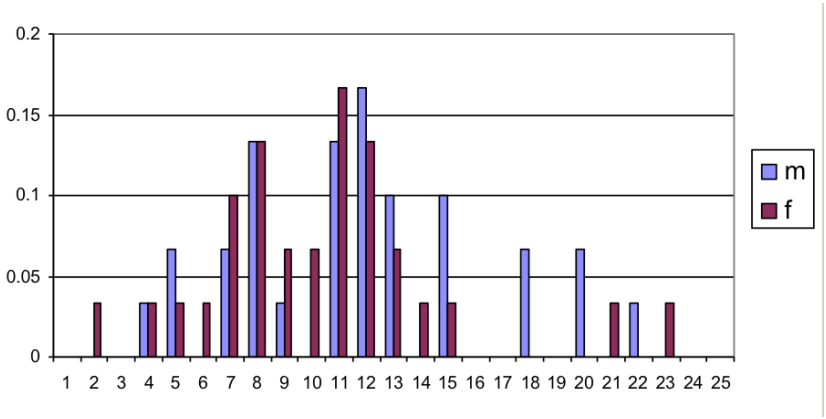
Gender Gap

- In summary:
  - Small, statistically insignificant gender gap under piece rate (11.23 vs 9.73, $p = 0.202$)
  - Larger, statistically significant gender gap under tournament (15.00 vs 10.9, $p < .01$)
- What could be causing this performance gender gap in one setting but not the other?

Two Additional Treatments

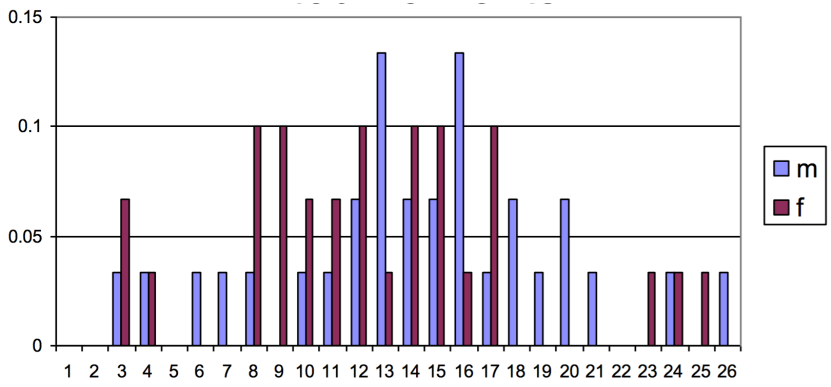
1. Uncertain payment
   - One person chosen at random and paid \$12 for each correct maze
   - Score is private
2. Single-sex tournament:
   - Groups of all 6 men or all 6 women
   - Payoff rules same as tournament treatment

Uncertain Payment



- Mean for men: 11.83, for women: 10.33. $p = 0.165$

Single-Sex Tournaments



- Mean for men: 14.3, for women: 12.6, $p = 0.135$

Summary of Results

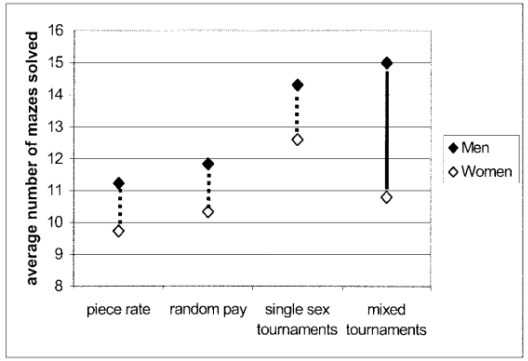


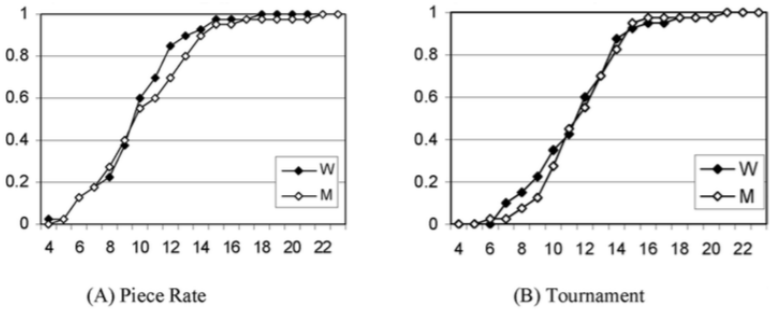
FIGURE III
Averages Performance of the 30 Men and 30 Women in Each of the Treatments

- Which theory is most consistent with data?

Selection into Competitive Environments

- Main results from previous paper: significant gender gap seems to exist only when women are competing directly against men
- Natural question: are women aware of this preference, and do they consider it when choosing which environments to enter?
- Research design by Niederle and Vesterlund (2007):
  - Groups of 4 (2 men, 2 women)
  - Different task: add groups of 5 two-digit numbers
  - As before, two treatments: piece-rate (50 cents per correct answer) and tournament (2 dollars per correct answer for winner only)
  - Initially, subjects randomly assigned into a treatment

Baseline Results: No Gender Gap in Performance



- Graphs show fraction of subjects completing at most that many sums correctly

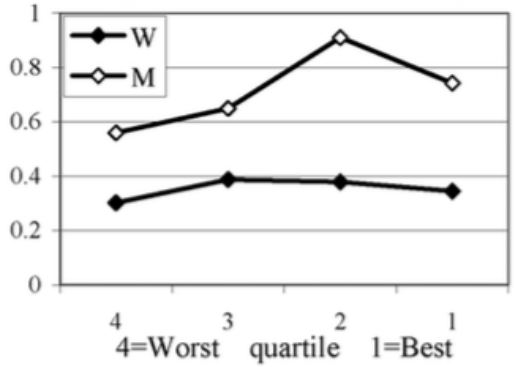
Selection Into Tournament

- After 5 rounds of either piece-rate or tournament, subjects get to choose between the two for the next part of the study
- Based on performance we see in baseline, women and men are expected to do equally well in the tournament
  - Top 30% of both genders should choose tournament
- What actually happens?

  % of women choose tournament
  % of men choose tournament

Likelihood to Enter Tournament

Men's likelihood to enter tournament increases with rank in baseline group, but women's likelihood does not:



What Could Cause Difference?

- Perhaps women have lower beliefs in their own ability (ie rank in baseline group)
- So, authors ask subjects to report what they *think* their rank is within their group of 4
  - Paid 1 dollar if correct, nothing otherwise

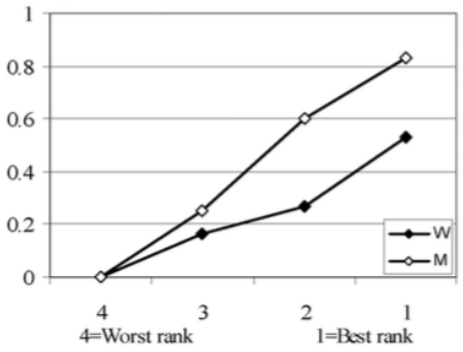
Men Supremely Over-Confident

DISTRIBUTION OF GUESSED TOURNAMENT RANK

	Men		Women	
	Guessed rank	Incorrect guess	Guessed rank	Incorrect guess
1: Best	30	22	17	9
2	5	3	15	10
3	4	2	6	5
4: Worst	1	1	2	1
Total	40	28	40	25

- If beliefs were correct on average, expect 10 guesses in each rank

Relative Confidence Does Not Fully Explain Gender Gap



- Graph plots likelihood of entering tournament as function of *guessed* rank in baseline