

# Econ 211

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# Discrimination

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  - ▶ A pure disutility for hiring, working with, or being around a certain group
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- ▶ Statistical discrimination
  - ▶ Membership in a certain group can be correlated with other characteristics that are relevant for hiring, eg education level
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  - ▶ Example? Higher car insurance premium for teenagers



# Are Emily and Greg More Employable Than Lakisha and Jamal?

- ▶ Want to examine racial discrimination in job hiring practices
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# Are Emily and Greg More Employable Than Lakisha and Jamal?

- ▶ Want to examine racial discrimination in job hiring practices
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- ▶ 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			African-American female		
Name	L(W)/L(B)	Perception White	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			African-American male		
Name	L(W)/L(B)	Perception White	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 ( <i>p</i> -value)
Sample:				
All sent resumes	9.65 [2,435]	6.45 [2,435]	1.50	3.20 (0.0000)
Chicago	8.06 [1,352]	5.40 [1,352]	1.49	2.66 (0.0057)
Boston	11.63 [1,083]	7.76 [1,083]	1.50	4.05 (0.0023)
Females	9.89 [1,860]	6.63 [1,886]	1.49	3.26 (0.0003)
Females in administrative jobs	10.46 [1,358]	6.55 [1,359]	1.60	3.91 (0.0003)
Females in sales jobs	8.37 [502]	6.83 [527]	1.22	1.54 (0.3523)
Males	8.87 [575]	5.83 [549]	1.52	3.04 (0.0513)

## ► Summary?

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- Summary? Resumes with white names 1.5 times more likely to get callback as identical resumes with black names

# 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 (0.03)	0.13 (0.04)	0.02 (0.03)
Years of experience <sup>2</sup> (*100)	-0.02 (0.01)	-0.04 (0.01)	-0.00 (0.01)
Volunteering? (Y = 1)	-0.01 (0.01)	-0.01 (0.01)	0.01 (0.01)
Military experience? (Y = 1)	-0.00 (0.01)	0.02 (0.03)	-0.01 (0.02)
E-mail? (Y = 1)	0.02 (0.01)	0.03 (0.01)	-0.00 (0.01)
Employment holes? (Y = 1)	0.02 (0.01)	0.03 (0.02)	0.01 (0.01)
Work in school? (Y = 1)	0.01 (0.01)	0.02 (0.01)	-0.00 (0.01)
Honors? (Y = 1)	0.05 (0.02)	0.06 (0.03)	0.03 (0.02)
Computer skills? (Y = 1)	-0.02 (0.01)	-0.04 (0.02)	-0.00 (0.01)
Special skills? (Y = 1)	0.05 (0.01)	0.06 (0.02)	0.04 (0.01)
<i>Ho</i> : Resume characteristics effects are all zero ( <i>p</i> -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

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- Summary? White names get much more credit for experience and education than black names

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

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Table 1

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

Gamble choice	Event	Probability (%)	Payoff		Expected payoff		Risk
			Loss framing (\$)	No-Loss framing (\$)	Loss framing (\$)	No-Loss framing (\$)	
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

Gamble choice	All subjects		Men		Women	
	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)

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  - ▶ Men appear less risk-averse
  - ▶ Men and women slightly more risk-seeking in losses than in gains
- ▶ 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?



# 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?
  - ▶ One possibility: different risk preferences as we just saw
  - ▶ Another possibility: men and women interact differently with competitive environments

# 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

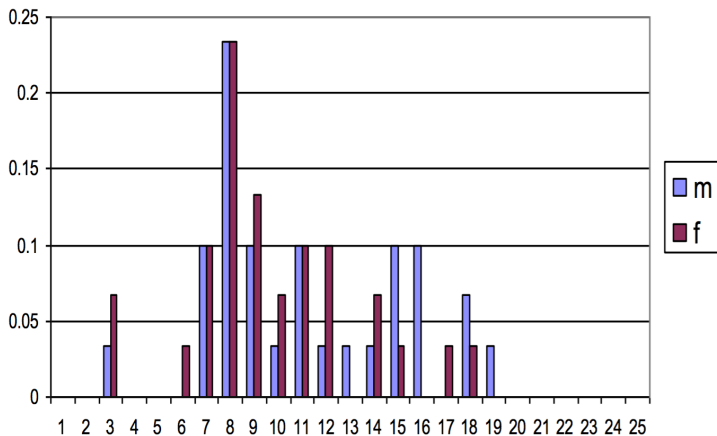
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    - ▶ Paid \$2 for every solved maze
    - ▶ Score is private

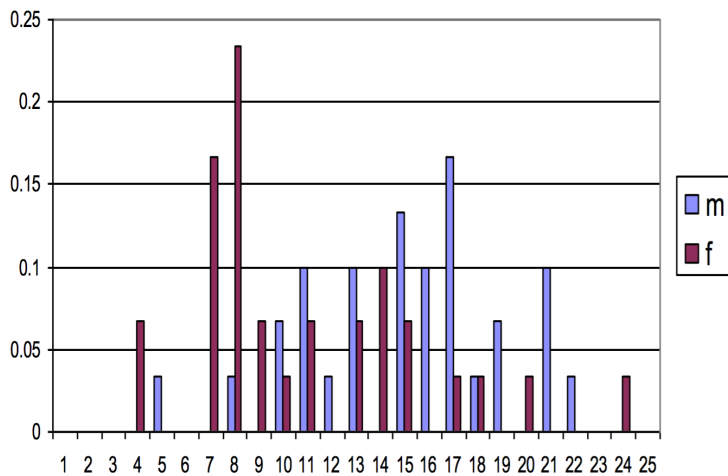
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  2. Competitive (tournament):
    - ▶ Person that solves most mazes in group gets \$12 for each maze solved
    - ▶ All others in group receive nothing
    - ▶ Winner anonymous

# 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?

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- ▶ What could be causing this performance gender gap in one setting but not the other?
  1. Women have maxed out their performance
  2. Women don't like competing
  3. Women don't like competing against men
  4. Women don't like uncertain payment



# Two Additional Treatments

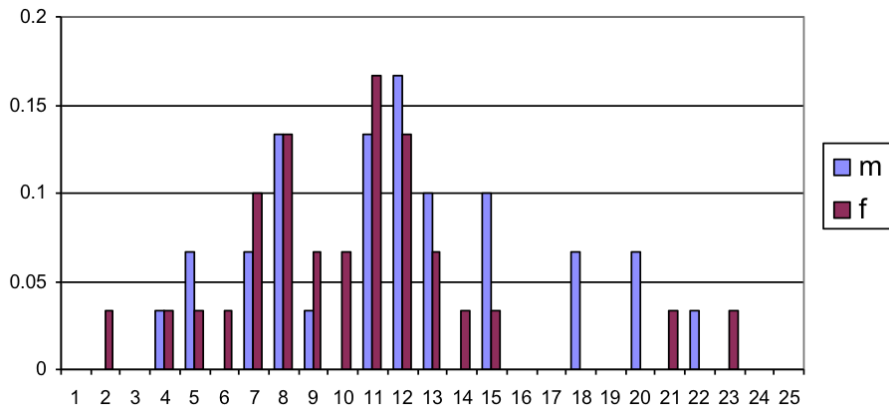
## 1. Uncertain payment

- ▶ One person chosen at random and paid \$12 for each correct maze
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# Two Additional Treatments

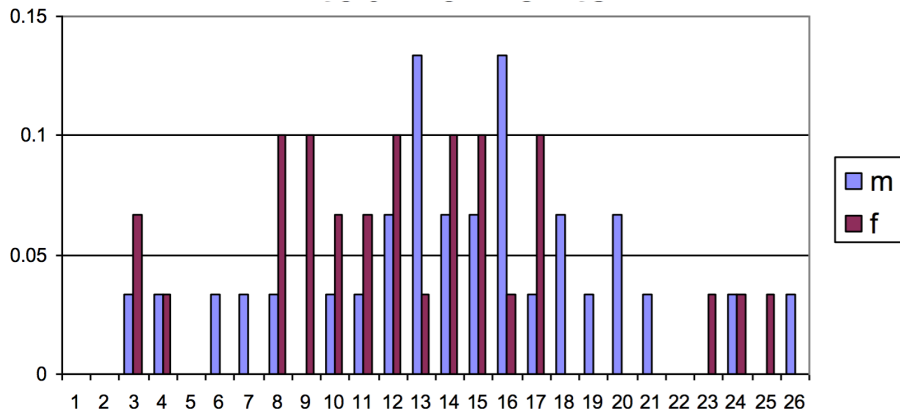
1. Uncertain payment
  - ▶ One person chosen at random and paid \$12 for each correct maze
  - ▶ Score is private
2. Single-sex tournament:
  - ▶ Groups of all 6 men or all 6 women
  - ▶ Payoff rules same as tournament treatment

# 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

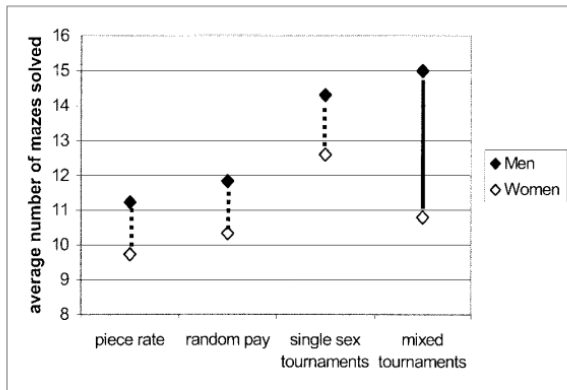


FIGURE III

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

- Which theory is most consistent with data?

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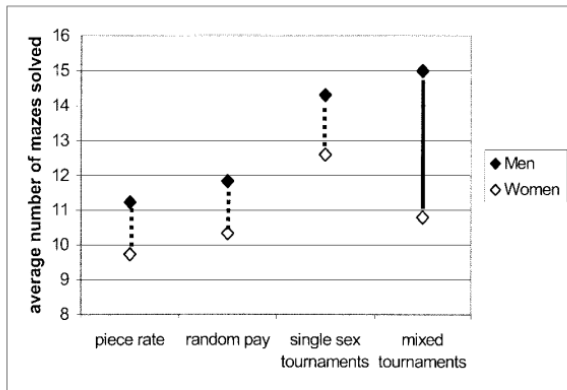


FIGURE III

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- ▶ Which theory is most consistent with data? Women don't like competing against men

# Selection into Competitive Environments

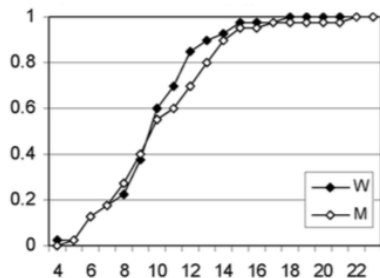
- ▶ Main results from previous paper: significant gender gap seems to exist only when women are competing directly against men
- ▶ Natural question: are women aware of this preference, and do they consider it when choosing which environments to enter?

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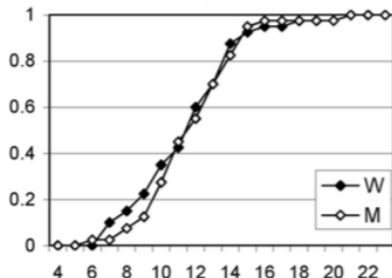
- ▶ Main results from previous paper: significant gender gap seems to exist only when women are competing directly against men
- ▶ Natural question: are women aware of this preference, and do they consider it when choosing which environments to enter?
- ▶ Research design by Niederle and Vesterlund (2007):
  - ▶ 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



(A) Piece Rate



(B) Tournament

- ▶ 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

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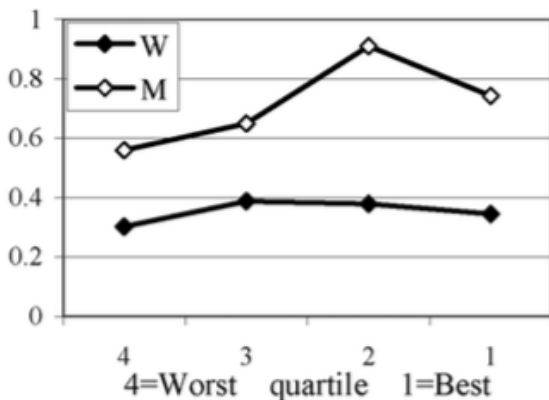
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  - ▶ Top 30% of both genders should choose tournament
- ▶ What actually happens?
  - ▶ 35% of women choose tournament
  - ▶ 73% of men choose tournament

# 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

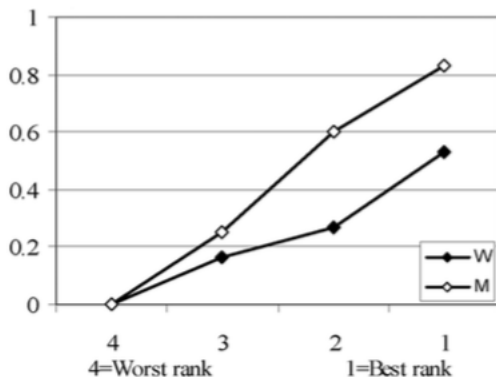
# Men Supremely Over-Confident

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