Chapter 9, part II

Po-Chun Huang
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Road map

Chapter 2 – Chapter 4: The basics

- Labor supply, labor demand, and equilibrium
- It gives us the basics for what determines the wage

The rest of the course mainly focuses on further reasons why wages differ across people

- Chapter 5: Compensating differentials
  - Differential job attributes can lead to wage differences
- Chapter 6: Human capital
  - Differential skill can lead to wage differences
- Chapter 7: Wage structure
- Chapter 8: Migration (covered during Chap. 4)
- Chapter 9: Labor Market Discrimination
  - Individual wages vary for seemingly irrelevant reasons (race, gender, national origin, sexual orientation…)

Outline

1. Evidence on discrimination

1. Evidence on discrimination

Observational evidence

Measuring discrimination

- If we use observational data, we need to adjust for other differences, such as in educational attain
- Our book goes through the Oaxaca-Blinder methodology, but recent research suggests a much easier approach works better…
- Estimate a Mincer equation and put in the characteristic of interest

$$\log w = \beta_0 + \beta_1 S + \beta_2 \exp + \beta_3 \exp^2 + \beta_4 Black + \beta_5 X + \varepsilon$$

- Interpretation: after adjusting for schooling, experience, and other characteristics (occupation, region, industry), do blacks systematically earn a different wage
- Pros: you can look at wage outcomes and adjust for anything you believe to be important
- Cons: Have we really adjusted for everything, such as preferences? Should one adjust for occupation?

Observational evidence

Measuring the determinants of a wage gap

- We are making an important shift here
- Previous slide: using a Mincer equation does not tell us about discrimination necessarily. Absolutely.
- A Mincer equation CAN tell us about the "determinants" of a wage
- "Explained" component
  - Background differences could be important—but are not <u>labor market discrimination</u>
  - Occupational differences could be important—and raise important questions
- "Unexplained" component could be discrimination, but could also be other reasonable factors that are not controlled for
- Our book refers to the Unexplained component as discrimination, but as the last slide makes clear (Section 9.8 of text), that may not be strictly correct

Black-white wage gap

In 1995, black workers earned 21 percent less than white workers

- Observation 1: any discrimination that occurs on the employment margin is missed in this gap
- Observation 2: some of this gap is related to observable characteristics
  - "Skill 1" (edu, age, sex, region): 8.2 ppt
  - "Skill 2" (1 + occ, ind): 11.4 ppt

TABLE 9-3 The Oaxaca Decomposition of the Black–White Wage Differential, 1995

Source: Joseph G. Altonji and Rebecca M. Blank, "Race and Gender in the Labor Market," in Orley Ashenfelter and David Card, editors, *Handbook of Labor Economics,* vol. 3C, Amsterdam: Elsevier, 1999, Table 5. The log wage differential between any two groups can be interpreted as being approximately equal to the percentage wage differential between the groups.

	Controls for Differences in Education, Age, Sex, and Region of Residence	Controls for Differences in Education, Age, Sex, Region of Residence, *and* Occupation and Industry
Raw log wage differential	−0.211	−0.211
Due to differences in skills	−0.082	−0.114
Due to discrimination	−0.134	−0.098

Black-white gap

Interpretation

- "Skill 1": lower bound for the amount of the gap that is not labor market discrimination—8.2 ppt
- "Skill 2": if ind/occ is a choice by employees, then the lower bound is 11.4 ppt. But occ?
- Using "Skill 2", we get 9.8 ppt is unexplained—and potentially is discrimination
  - This remaining gap is large enough to be alarming…

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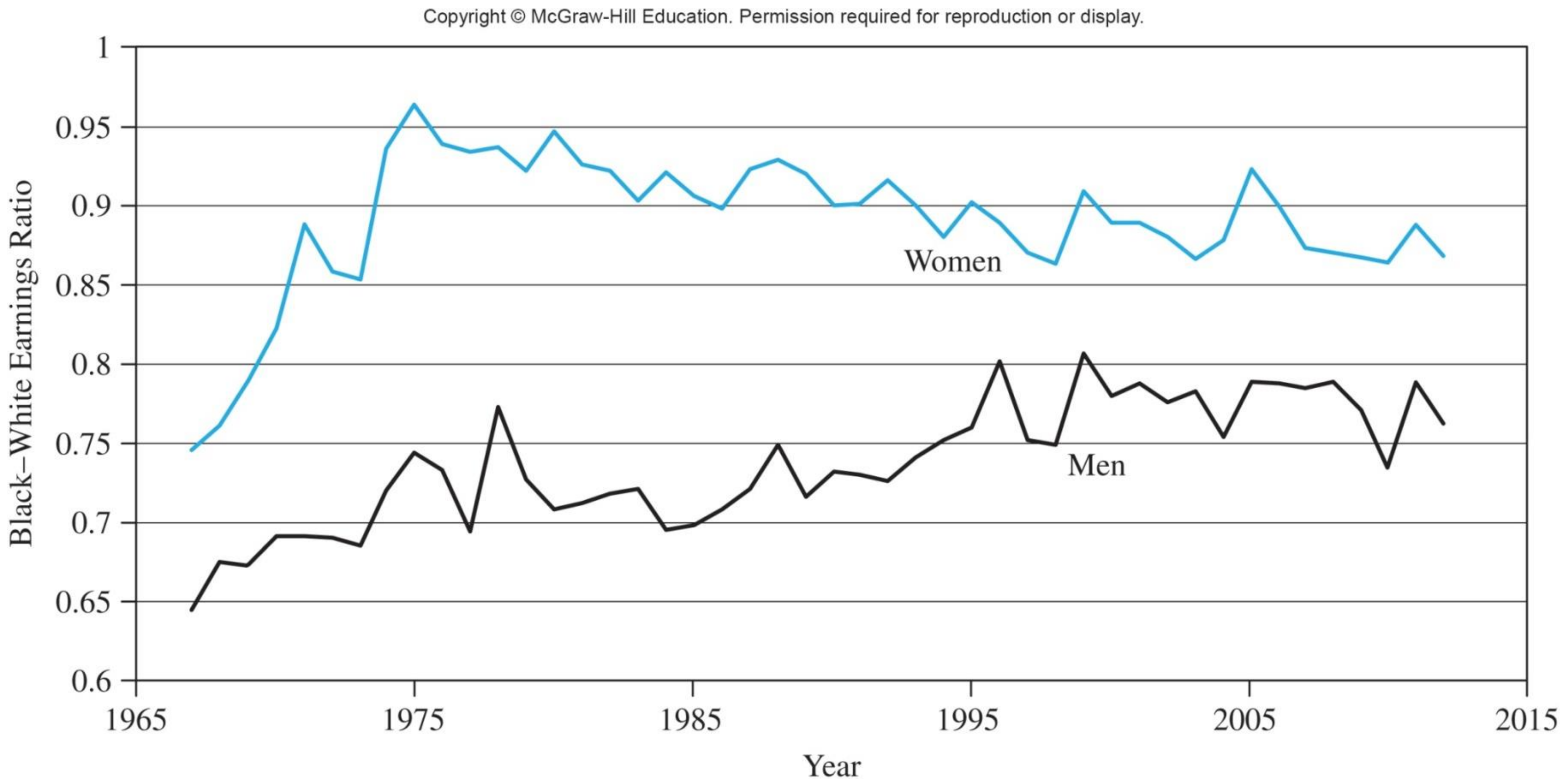
Black-white gap



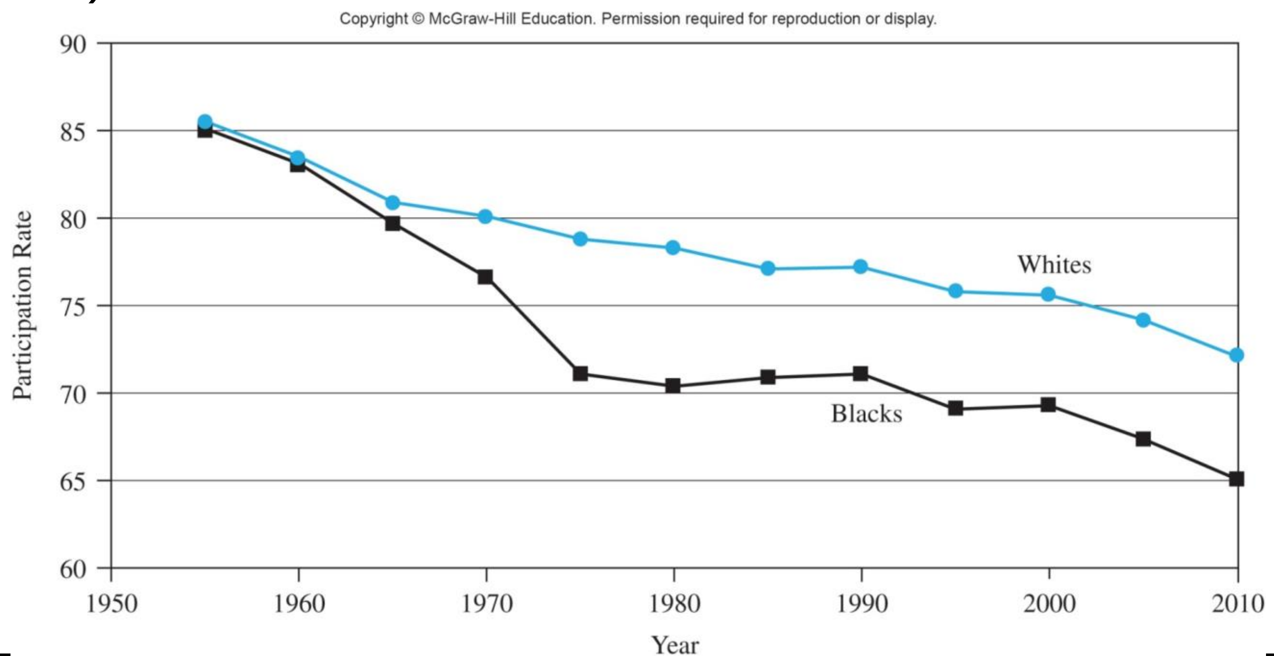
Ratio increased markedly post-Civil Rights Act, and continued to increase for men but not for women

Estimates from elsewhere: increasing quantity and quality of schooling can explain at least of the convergence

Black-white gap

Despite increase in black wages, there has been a very troubling trend: a large decline in LFP

- Whites declined too, just not as much
- If the "missing blacks" were the least skilled, it might be the source of the improving wage gap
- Studies find that between 1/3 to all of gap improvement could be due to this change (i.e., perhaps discrimination has not declined)



Black-white gap

AFQT studies

- Recall that the “unexplained” gap could be discrimination or just unmeasured skill
- Neal/Johnson find that only a 5 ppt gap between blacks and whites (down from 20 ppt) after the AFQT is entered in the model
- Interpretation: AFQT measures additional skill (whether innate or obtained in school), so perhaps there is less discrimination in the labor market

Skin color

- So far we have focused on the black-white gap
- Several studies show that skin-tone matters, even after controlling for education
- Example: Whites $15.94, light tone $14.42, medium tone $13.23, dark tone $11.72.
- What does this mean…?

Female-male gap

- Same methods, but different gap
  - Overall gap: 28.6 ppt
  - Adjusting for Skill 1: Unexplained gap is 27.9 ppt
    - Why so similar? Education is similar, and these models use “potential experience” (Age-Education-5) because actual experience is not known
  - Adjusting for Skill 2: Unexplained gap is 21.1 ppt
    - But if discrimination operates through occupation…

TABLE 9-5 The Oaxaca Decomposition of the Female–Male Wage Differential, 1995

Source: Joseph G. Altonji and Rebecca M. Blank, “Race and Gender in the Labor Market,” in Orley Ashenfelter and David Card, editors, *Handbook of Labor Economics*, vol. 3C, Amsterdam: Elsevier, 1999, Table 5. The log wage differential between any two groups can be interpreted as being approximately equal to the percentage wage differential between the groups.

	Controls for Differences in Education, Age, Sex, and Region of Residence	Controls for Differences in Education, Age, Sex, Region of Residence, *and* Occupation and Industry
Raw log wage differential	−0.286	−0.286
Due to differences in skills	−0.008	−0.076
Due to discrimination	−0.279	−0.211

Female-male gap

The big issue: potential vs. actual experience

- Many women take time off mid-career
  - This provides less incentive to accumulate OJT human capital
  - All human capital might depreciate—how much it depreciates becomes important to the calculation
- Disentangling the role of actual experience is difficult because it adjusts the incentives of women and employers
  - Might employers provide different assignments?
  - Might women behave differently?

Some “experimental” evidence

- Blinded auditions at orchestras increased probability of women advancing out of initial rounds by 50%
- Same problem as other experiments: How does this relate to the wage gap?

Female-male gap

Occupational crowding

- Substantial evidence of occupational segregation
- Substantial evidence that "female occupations" pay less, for both men and women

TABLE 9-6
Female Employment in 2009, by Occupation

Occupation	Percent Female	Median Weekly Earnings
Carpenters	1.6%	$623
Aircraft mechanics	3.8	980
Truck drivers	5.2	686
Police and sheriff's patrol officers	15.5	961
Chemical engineers	18.4	1,505
Architects	25.3	1,209
Lawyers	32.4	1,757
Physicians	32.2	1,975
Security guards	21.9	507
Cooks	41.5	393
Postal clerks	49.6	915
Financial managers	54.7	830
Real estate sales	54.6	820
Teachers: secondary school	54.9	987
Teachers: elementary school	81.9	946
Maids and housemen	89.8	387
Tellers	87.0	487
Child care workers	95.0	400
Receptionists	91.5	530
Teachers: kindergarten	97.8	621

Sources: U.S. Department of Commerce, *Statistical Abstract of the United States, 2011*, Washington, DC: Government Printing Office, 2011, Table 615; U.S. Department of Labor, Bureau of Labor Statistics, Occupational Earnings Data, Table 39. Median weekly earnings of full-time wage and salary workers by detailed occupation and sex, 2009, see www.bls.gov/emp/ep_sources_earnings.htm.

Female-male gap

Occupational crowding

- It could be active labor market discrimination
  - Women are steered to low-wage occupations
- It could be pre-labor market discrimination with labor market consequences
  - Society/schools systematical steer women to some occupations, which depresses those wages
- It could be tastes…

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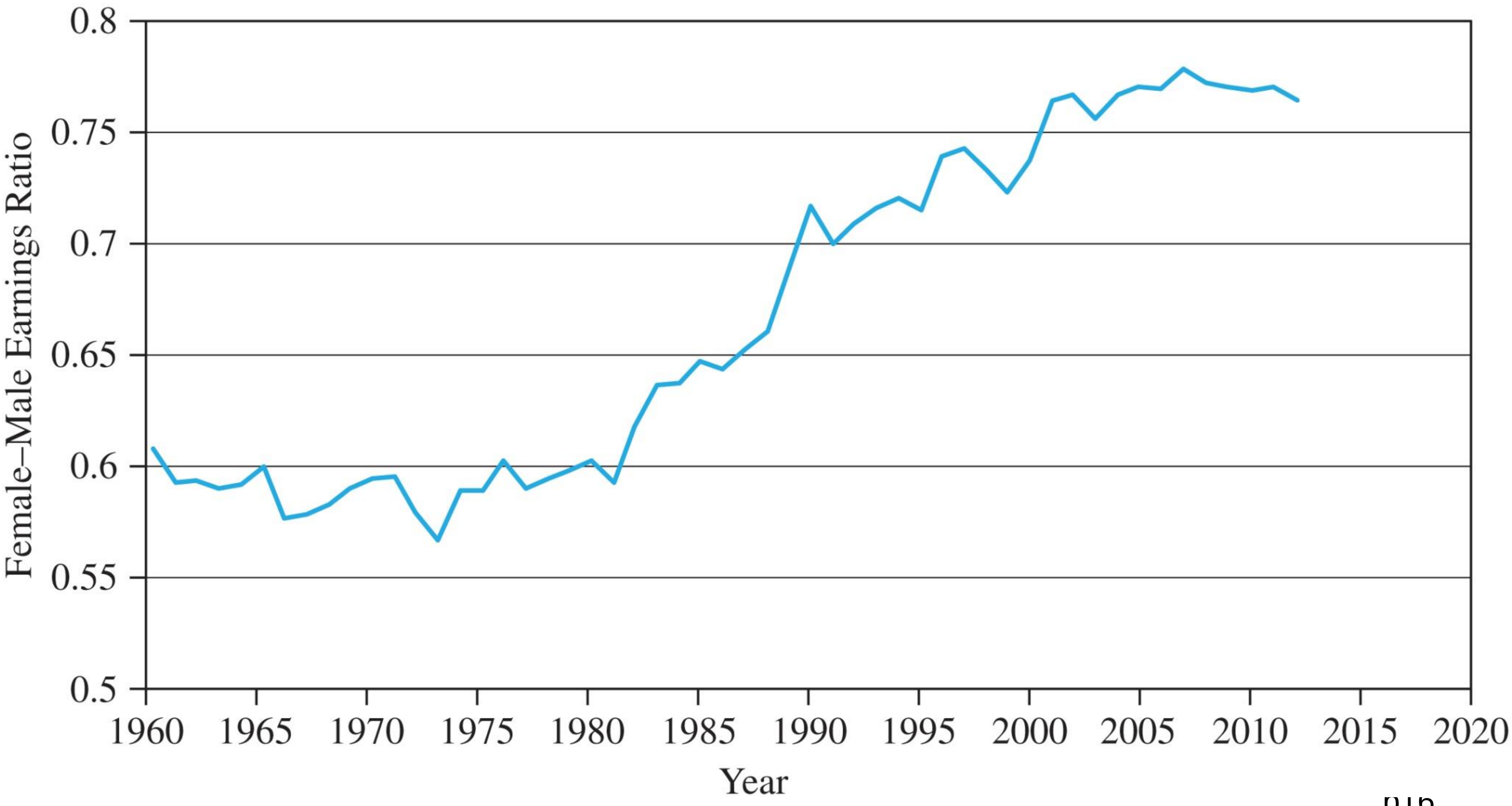
Female-male gap

The gap over time

- Substantial improvements, but a substantial gap remains



Female-male gap

Some parting comments

- The previous picture masks some convergence
- Why? There was substantial increases in employment, and these women systematically looked different (education, experience, age, etc.)
- About half of the improvement in the wage gap was due to increased labor market experience of women
- These trends probably have implications for Chapter 7
  - Chap 7: How do S/D affect the wage structure?
  - Women entering the labor force certainly affected S
  - Women entering the labor force certainly affected D, as market production replaced home production
  - Untangling these issues is very difficult….

Experimental evidence

Resume example by Bertrand and Mullanaithan

- Send 5,000 fake resumes to 1,300 jobs in Boston and Chicago
- Randomly assign the name to be "Emily Walsh" vs. "Lakisha Washington" or "Greg Baker" vs. "Jamal Jones"
  - They also randomly assigned skills (experience, degree certification, foreign language)
- Sit back and see who gets called back
- Result
  - White-sounding names got one callback per 10 resumes sent, black-sounding names got one callback per 15 resumes
  - To put this in context, 5 more call backs was what 8 years of additional experience delivered

Stunning: 50% more resumes to get the same number of call-backs, which is the same as 8 years of experience…

Experimental evidence

Pros of resume methodology

- Solid identification
- Clear evidence about discrimination in the initial callback process

Cons of resume methodology

- It only tells us about the callback process for initial entry into firms
- It might not translate to wages: Perhaps Jamal is searching for the non-discriminatory firms, and there are enough of them so that there are not wage differences. It is not the average that matters, it is the marginal firm

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	

Notes: This table tabulates the different first names used in the experiment and their identifiability. The first column reports the likelihood that a baby born with that name (in Massachusetts between 1974 and 1979) is White (or African-American) relative to the likelihood that it is African-American (White). The second column reports the probability that the name was picked as White (or African-American) in an independent field survey of people. The last row for each group of names shows the proportion of all births in that race group that these names account for.

Callback rates

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.

How does quality matter?

Quality: more labor market experience, fewer holes, have email address, list some computer skills, list other skills (foreign language); <u>on average, education is same</u>

Findings

- Quality matters
- Quality matters more for whites than for blacks

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)				
	Low	High	Ratio	Difference (*p*- value)
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)

All results

Is there discrimination?

- Callback rate: Whites 9.7 percent, Black 6.5 percent
- Small differences by gender

Answer vary by quality of resume?

- High quality resumes mean more for whites than blacks

Applicant's address

- Better neighborhoods matter, but equally for whites and blacks

Job/employer characteristic

- No differences across occupation and job requirements
- No difference if employer lists no discrimination clause
- No difference for federal contractors

Counter arguments

Firms are following very strict "call back rules" based on the population characteristics and they received many other resumes from blacks.

- Such an argument is inconsistent with similar callback rates across all industries, with some having very large racial imbalances

Might names be signaling something else?

- Do economically disadvantaged blacks pick distinctively black names and employers know this?
- Possible, but addresses didn't matter by race
- Another analysis looking at economic circumstances of name—no real evidence

But this is just the callback stage. Would it matter for wages?

- Would you want to have to send out 50% more resumes…?

Experimental evidence

Audit studies

- Long history, going back to discrimination in housing market in the 1960s
- Send out matched pairs with identical credentials to apply for jobs
- Example: 1989 Chicago and San Diego, neatly dressed, 22 year old, no criminal record, some college credits, some work experience as a stock person or waiter. Main difference between matched pairs: one was Hispanic with a slight Spanish accent, dark hair, and light brown skin, and the other was non-Hispanic white with no accent, and brown/blonde/red hair
  - Result: White applicant was 33 more likely to be interviewed and 52 percent more likely to receive a job offer
- Audit studies have studied ethnicity, race, and gender

Experimental evidence

Pros of audit methodology

- We can look beyond callback to actual hiring
- We can experimentally vary different how ethnicity / race / gender is presented: Should it matter if the dress is different (black and khakis vs. black and baggy pants)?

Cons of audit methodology

- Vs. resumes: do the pairs REALLY act identically?
- Although it gets beyond callback, the same cons exist as the resume methodology: it might not translate into wage differences because it is the marginal firm that matters

Bottom line: resume and audit methodology suggests disparate treatment in the margins they can study