Economics of Discrimination

Part 2

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Correspondence experiments

- Instead of training pairs of actors, we create fictitious resumes and apply with them to companies.
- We gain perfect control:
  - Over the group-signal through manipulation of name
  - No experimenter demand effect
- Bertrand and Mullainathan (2004) one of the first such studies

Bertrand and Mullainathan (2004)

- 4890 fictitious resumes are sent by mail in response to help-wanted ads in Chicago and Boston newspapers.
- Half of the applications randomly assigned a white sounding name, the other half an African-American name (multiple names for each group)
- Each job opening received four different applications:
  - Two white sounding names and two African-American sounding names
  - Two high quality applications and two low quality applications
  - Always one white sounding and one African- American sounding application with a high quality

Bertrand and Mullainathan (2004): resumes

TABLE 3—RESUME CHARACTERISTICS: SUMMARY STATISTICS

Sample:	All resumes	White names	African-American	Higher quality	Lower quality
Characteristic:					
College degree	0.72	0.72	0.72	0.72	0.71
(Y = 1)	(0.45)	(0.45)	(0.45)	(0.45)	(0.45)
Years of experience	7.84	7.86	7.83	8.29	7.39
	(5.04)	(5.07)	(5.01)	(5.29)	(4.75)
Volunteering experience?	0.41	0.41	0.41	0.79	0.03
(Y = 1)	(0.49)	(0.49)	(0.49)	(0.41)	(0.16)
Military experience?	0.10	0.09	0.10	0.19	0.00
(Y = 1)	(0.30)	(0.29)	(0.30)	(0.39)	(0.06)
E-mail address?	0.48	0.48	0.48	0.92	0.03
(Y = 1)	(0.50)	(0.50)	(0.50)	(0.27)	(0.17)
Employment holes?	0.45	0.45	0.45	0.34	0.56
(Y = 1)	(0.50)	(0.50)	(0.50)	(0.47)	(0.50)
Work in school?	0.56	0.56	0.56	0.72	0.40
(Y = 1)	(0.50)	(0.50)	(0.50)	(0.45)	(0.49)
Honors?	0.05	0.05	0.05	0.07	0.03
(Y = 1)	(0.22)	(0.23)	(0.22)	(0.25)	(0.18)
Computer skills?	0.82	0.81	0.83	0.91	0.73
(Y = 1)	(0.38)	(0.39)	(0.37)	(0.29)	(0.44)
Special skills?	0.33	0.33	0.33	0.36	0.30
(Y = 1)	(0.47)	(0.47)	(0.47)	(0.48)	(0.46)
Fraction high school dropouts in	0.19	0.19	0.19	0.19	0.18
applicant's zip code	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Fraction college or more in	0.21	0.21	0.21	0.21	0.22
applicant's zip code	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)
Fraction Whites in applicant's zip	0.54	0.55	0.54	0.53	0.55
code	(0.33)	(0.33)	(0.33)	(0.33)	(0.33)
Fraction African-Americans in	0.31	0.31	0.31	0.32	0.31
applicant's zip code	(0.33)	(0.33)	(0.33)	(0.33)	(0.33)
Log(median per capital income)	9.55	9.55	9.55	9.54	9.56
in applicant's zip code	(0.56)	(0.56)	(0.55)	(0.54)	(0.57)
Sample size	4,870	2,435	2,435	2,446	2,424

Notes: The table reports means and standard deviations for the resume characteristics as listed on the left. Column 1 refers to all resumes sent; column 2 refers to resumes with White names; column 3 refers to resumes with African-American names; column 4 refers to higher-quality resumes; column 5 refers to lower-quality resumes. See text for details.

Bertrand and Mullainathan (2004): names used

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.

Bertrand and Mullainathan (2004): sending resumes to ads

- All employment ads in the Sunday editions of *The Boston Globe* and *The Chicago Tribune* in sales, administrative support, and clerical and customer services sections received the set of resumes
  - Ad characteristics recorded (to serve as controls / for heterogeneity analysis)
  - Excluding all ads that asked applicants to call
- Callbacks and email responses of employers as the dependent variables (can record phone callbacks)
  - Polished design: Outgoing message on mailboxes uses the voice of someone of the appropriate race and gender

Bertrand and Mullainathan (2004): results

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.

Bertrand and Mullainathan (2004): returns to quality

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

	Panel A: Subjective Measure of Quality (Percent Callback)			
	Low	High	Ratio	Difference (p-value)
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)

Bertrand and Mullainathan (2004): issues

- Outcome measure only for first stage, not ultimate job offer
- Only newspaper ads used (e.g. more conservative firms post announcements in newspaper; race specific job search channels?)
- Treatment is not "race" but race-specific-names. Other confounds?

Bertrand and Mullainathan (2004): socio-economic status?

TABLE 8—CALLBACK RATE AND MOTHER'S EDUCATION BY FIRST NAME

White female			African-American female		
Name	Percent callback	Mother education	Name	Percent callback	Mother education
Emily	7.9	96.6	Aisha	2.2	77.2
Anne	8.3	93.1	Keisha	3.8	68.8
Jill	8.4	92.3	Tamika	5.5	61.5
Allison	9.5	95.7	Lakisha	5.5	55.6
Laurie	9.7	93.4	Tanisha	5.8	64.0
Sarah	9.8	97.9	Latoya	8.4	55.5
Meredith	10.2	81.8	Kenya	8.7	70.2
Carrie	13.1	80.7	Latonya	9.1	31.3
Kristen	13.1	93.4	Ebony	9.6	65.6
Average		91.7	Average		61.0
Overall		83.9	Overall		70.2
Correlation	−0.318	(p = 0.404)	Correlation	−0.383	(p = 0.309)

White male			African-American male		
Name	Percent callback	Mother education	Name	Percent callback	Mother education
Todd	5.9	87.7	Rasheed	3.0	77.3
Neil	6.6	85.7	Tremayne	4.3	—
Geoffrey	6.8	96.0	Kareem	4.7	67.4
Brett	6.8	93.9	Darnell	4.8	66.1
Brendan	7.7	96.7	Tyrone	5.3	64.0
Greg	7.8	88.3	Hakim	5.5	73.7
Matthew	9.0	93.1	Jamal	6.6	73.9
Jay	13.4	85.4	Leroy	9.4	53.3
Brad	15.9	90.5	Jermaine	9.6	57.5
Average		91.7	Average		66.7
Overall		83.5	Overall		68.9
Correlation	−0.0251	(p = 0.949)	Correlation	−0.595	(p = 0.120)

Notes: This table reports, for each first name used in the experiment, callback rate and average mother education. Mother education for a given first name is defined as the percent of babies born with that name in Massachusetts between 1970 and 1986 whose mother had at least completed a high school degree (see text for details). Within each sex/race group, first names are ranked by increasing callback rate. "Average" reports, within each race-gender group, the average mother education for all the babies born with one of the names used in the experiment. "Overall" reports, within each race-gender group, average mother education for all babies born in Massachusetts between 1970 and 1986 in that race-gender group. "Correlation" reports the Spearman rank order correlation between callback rate and mother education *within* each race-gender group as well as the p-value for the test of independence.

Correspondence studies: theories?

- The paper credibly documents extent of discrimination in the particular market. Many other papers check other groups (gender, sexual orientation, religion) in many markets (see Bertrand and Duflo 2017 for a comprehensive review).
- But can it distinguish between respective theories? Why useful? For policy:
  - If statistical, providing more information can help.
  - If taste-based, more education / psychological training needed.

Attention discrimination

- In Bartoš, Bauer, Chytilová, and Matějka (2016), we use a correspondence experiment to understand underlying theories.
  - Motivation: note the differential responsiveness to returns to quality by whites / blacks in Bertrand and Mullainathan (2004)?
  - Further, recall: both models (statistical / taste-based) assume that once information about applicants is available, employers process it completely.
  - But is this realistic? Information processing is costly. Hence, attention is scarce and affects decision-making (Kahneman 1973, Sims 2003).
  - We present:
    1. A model of discrimination and scarce attention, and
    2. Three correspondence field experiments in two countries, which monitor information acquisition about applicants, and
    3. Three online surveys reinforcing the findings.

Attention discrimination

- Note: For the sake of time, I drop the German experiment, I'll be quick on the model, and I won't discuss the online surveys in detail.

Attention to information during the selection process

"They [human resource staff] look at a CV for ten seconds and then decide whether or not to continue reading. If they do, they read for another 20 seconds, before deciding again whether to press on, until there is either enough interest to justify an interview or to toss you into the 'no' pile." (The Economist 2012)

The model: setup

- Two stage model:
    1. Screening stage
    2. Interview stage (final decision to accept or reject applicant)
- In the first stage decision maker (DM) decides whether to:
    1. Acquire available information about the applicant
    2. Invite the applicant for an interview

    - Level of attention to available information endogenous to *a priori* observable group G of the applicant

The model: signal precision

- Applicant's payoff to firm: $\pi = q - d_G$ where:
  - $q \ldots$ objective quality (unobservable)
  - Initially (without any information): $q \sim N(q_G, \sigma_G^2)$
  - $d_G \ldots$ distaste towards applicant's group G (of the employer or of those employer relies on - customers)
- Additional applicant's information improves signal precision: $q = q_g + q_1 + q_2$
  - $q_i \ldots$ signal precision in stage i
  - $q_1 \sim N(q_1, \sigma_{G,1}^2)$; independent from q_2
  - For simplicity we assume that q is revealed in the second stage
  - *Note:* information acquisition costs C_1 and C_2, respectively

The model: payoff maximization

- DM: $max\Big\{E[Payoff] - C_1\mathbf{I}\{search\} - C_2\mathbf{I}\{interview\}\Big\}$,

$$Payoff = \begin{cases} \pi: & \text{if the DM accepts the applicant} \\ R: & \text{if the DM rejects the applicant} \end{cases}$$

  - $R\ldots$ Reservation quality (or cost of further search)
  - $C_i\ldots$ Cost of information acquisition, reveals $q_i,\ i \in \{1;2\}$

- DM's posterior after the first stage:
  - Screening: $N(q_G + q_1, \sigma_G^2 - \sigma_{G,1}^2)$
  - No screening: $N(q_G, \sigma_G^2)$
  - Given the posterior, DM chooses whether to interview the applicants (costs C_2)
- After the interview, DM decides whether to accept the applicant: acceptance if $q - d_G > R$

The model: selection scenaria

- There are three possible scenaria for DM in the first stage (only G observed). DM compares them:
    1. $Payoff(reject) = R$
    2. $Payoff(invite) = E\Big[max(R, q - d_G)\Big] - C_2$
    3. $Payoff(info) = E\Big[max(R, E[max(R, q - d_G)|q_1] - C_2)\Big] - C_1$

The model: markets

- **Cherry-picking markets**: aim is to select only superstars: pay attention to those that a priori seem they might be the superstars.
  - $Payoff(reject) > Payoff(invite)$

- **Lemon-dropping markets**: aim is to select most of the candidates: pay attention to those that a priori seem they might not be good enough, the a priori above average ones are most likely to be good enough anyway.
  - $Payoff(reject) < Payoff(invite)$

Theories of discrimination and the model

- **Taste-based discrimination (Becker 1971)**
  - $d_G \ldots$ Becker's distaste parameter
    - Higher C_2 similar to d_G (lower willingness to interact with group G applicants)
  - Increase in d_G or $C_2 \Rightarrow$ different predictions across market types:
    - **Cherry picking market**: relatively less attention (DMs' status quo is to reject, information acquired only if expected to alter status quo)
    - **Lemon dropping market**: relatively more attention (DMs only seek bad apples)

Theories of discrimination and the model

- **Statistical discrimination (Phelps 1972, Arrow 1973)**
  - Represented by change in q_G or σ_G^2
  - Drop in q_G similar to an increase in d_G (from profit function)
  - Decrease in σ_G^2 (holding $\sigma_{G,1}^2$ constant) similar to a decrease in q_G since lower σ_G^2 decreases the likelihood of good candidates in the population
  - Predictions for $q_G \downarrow$ or $\sigma_G^2 \downarrow$:
    - **Cherry picking market**: relatively less attention
    - **Lemon dropping market**: relatively more attention

Theories of discrimination and the model

- **Greater difficulty to understand signals from dissimilar groups (Cornell and Welsh 1996)**
  - Would be represented by lower $\sigma^2_{G,1}$ (resumes do not help to change priors) or higher C_1
    - *Note 1*: both variables affect *payoff* (*info*) only
    - *Note 2*: d_G, q_G, σ^2_G, C_2 also affect *payoff* (*invite*), i.e. a priori attractiveness of the group
  - Prediction:
    - Both markets: attention relatively (weakly) decreases

Proposition 1: Market types and endogenous attention

- The above discussed channels lead to testable predictions:
  1. Higher d_G, and C_2, or lower σ_G^2, and q_G lead to less attention in cherry picking markets and more attention in the lemon-dropping markets
  2. Applicants with higher C_1 or lower $\sigma_{G,1}^2$ paid less attention in both markets (difficulty to screen dissimilar applicants)

Market types, endogenous attention, and decisions

- **Cherry picking market**:
  - Without additional information, applicant rejected
  - With DM's attention chance of invitation increases
- **Lemon dropping market**:
  - *A priori payoff* $(reject) <$ *payoff* $(invite)$
  - More attention decreases likelihood of invitation

Questions for experiments

1. Are ethnic minorities discriminated against in selection decisions?
2. Does ethnicity of applicant affect the level of attention to available information?
   - Less attention to minorities on markets where only top applicants are selected from a large pool of applicants?
   - More attention to minorities when most applicants are selected?
3. Can differences in attention explain difference in returns to applicant's quality?

Czech rental housing market experiment (N=1793)

- Expressing interest in flat visit in Czech Republic, based on offers on major websites facilitating flat rental.
- To evoke ethnic status, we varied applicant's name.
  - White majority, Asian minority name, Roma minority name
- Manipulating access to information about applicant:
  - **No Information Treatment:** *"Dear Sir/Madam, I am writing because I am very interested in renting the apartment that you have advertised. When would be a good time to come see the apartment? Best regards, Phan Quyet Nguyen"*
  - **Monitored information Treatment:** *"... Best regards, Phan Quyet Nguyen, phan.quyet.nguyen.sweb.cz"*

Outcomes of interest

- Measures of information acquisition:
  - Likelihood of opening a personal website.
  - Number of pieces of information acquired on the website.
- Selection decision:
  - Invitation for a flat visit.

Effect of name on invitation rate

	(1)	(2)	(3)	(4)
Panel A: Landlord's selection decision				
Dependent variable:	**Invitation for an apartment viewing**			
Sample:	No Information Treatment		White majority name	Ethnic minority name
Ethnic minority name	-0.39***			
	-0.044			
Asian minority name		-0.41***		
		-0.054		
Roma minority name		-0.39***		
		-0.054		
Monitored Information Treatment			-0.06	0.08**
			-0.045	-0.036
Additional text in the email – with high school			0.00	0.08*
			-0.056	-0.046
Additional text in the email – with college			0.01	0.15***
			-0.058	-0.046
Mean of the dep. var.	0.53	0.53	$\boxed{0.78}$	0.41
Observations	451	451	599	1,194

Landlords are not very selective –
most applicants are invited

Effect of name on invitation rate

	(1)	(2)	(3)	(4)
Panel A: Landlord's selection decision				
Dependent variable:	**Invitation for an apartment viewing**			
Sample:	No Information Treatment		White majority name	Ethnic minority name
Ethnic minority name	-0.39***			
	-0.044			
Asian minority name		-0.41***		
		-0.054		
Roma minority name		-0.39***		
		-0.054		
Monitored Information Treatment			-0.06	0.08**
			-0.045	-0.036
Additional text in the email – with high school			0.00	0.08*
			-0.056	-0.046
Additional text in the email – with college			0.01	0.15***
			-0.058	-0.046
Mean of the dep. var.	0.53	0.53	0.78	0.41
Observations	451	451	599	1,194

Minities are discriminated

Effect of name on information acquisition

Panel B: Information acquisition								
Dependent variable:	A landlord opens applicant's pers. webpage		Sum of information paid attention to		Acquiring information about education and occupation (sum)		Acquiring information about personal characteristics (sum)	
Sample:	Monitored Information Treatment – all observations				Monitored Information Treatment – sub-sample of landlords who opened applicant's website			
Ethnic minority name	0.08**		0.46***		0.18**		0.12	
	(0.037)		(0.163)		(0.085)		(0.126)	
Asian minority name		0.05		0.31		0.17*		0.07
		(0.045)		(0.192)		(0.098)		(0.141)
Roma minority name		0.11***		0.60***		0.18*		0.15
		(0.043)		(0.191)		(0.095)		(0.138)
Mean of dep. var.	0.38	0.38	1.54	1.54	1.68	1.68	2.47	2.47
Observations	762	762	762	762	293	293	293	293

Landlords acquire more information about minority applicants

Responsiveness to available information

	(1)	(2)	(3)	(4)
Panel A: Landlord's selection decision				
Dependent variable:	**Invitation for an apartment viewing**			
Sample:	No Information Treatment		White majority name	Ethnic minority name
Ethnic minority name	-0.39***			
	-0.044			
Asian minority name		-0.41***		
		-0.054		
Roma minority name		-0.39***		
		-0.054		
Monitored Information Treatment			-0.06	0.08**
			-0.045	-0.036
Additional text in the email – with high school			0.00	0.08*
			-0.056	-0.046
Additional text in the email – with college			0.01	0.15***
			-0.058	-0.046
Mean of the dep. var.	0.53	0.53	0.78	0.41
Observations	451	451	599	1,194

Higher responsiveness to manipulations of information about minorities

Online survey among landlords: perceptions

Expected overall quality (q_G- d_G) higher for the majority applicant	White majority name (W) (1)	Ethnic minority name (E) (2)	Difference: W-E p-value (3)
Panel A: Survey among decision-makers in the rental housing market			
Expected applicant's overall quality	$\boxed{3.57}$	$\boxed{3.04}$	0.53 (0.01)
Standard deviation of applicant's expected overall quality	0.63	0.62	0.01 (0.94)
Expected informativeness of applicant's personal website	2.66	2.62	0.04 (0.85)
Observations	29	60	

Online survey among landlords: perceptions

SD of applicant's expected quality (σ_G^2) the same across groups

	White majority name (W) (1)	Ethnic minority name (E) (2)	Difference: W-E p-value (3)
Panel A: Survey among decision-makers in the rental housing market			
Expected applicant's overall quality	3.57	3.04	0.53 (0.01)
Standard deviation of applicant's expected overall quality	0.63	0.62	0.01 (0.94)
Expected informativeness of applicant's personal website	2.66	2.62	0.04 (0.85)
Observations	29	60	

Online survey among landlords: perceptions

Cost of information acquisition (C_1 or $\sigma^2_{G,1}$) equal for both groups

	White majority name (W) (1)	Ethnic minority name (E) (2)	Difference: W-E p-value (3)
Panel A: Survey among decision-makers in the rental housing market			
Expected applicant's overall quality	3.57	3.04	0.53 (0.01)
Standard deviation of applicant's expected overall quality	0.63	0.62	0.01 (0.94)
Expected informativeness of applicant's personal website	2.66	2.62	0.04 (0.85)
Observations	29	60	

Czech labor market experiment (N=274)

- We responded to ads posted on online job site:
  - Administration, marketing, sales, services, logistics.
  - *"Dear Sir/Madam, I am writing because I am very interested in the Real Estate Agent job position advertised by your company. You can find my resume in this hyperlink: phanquyetnguyen1982.sweb.cz. Best regards, Phan Quyet Nguyen"*
- Outcomes:
  - Likelihood of opening a resume.
  - Acquiring more information about the applicant – learning more about each of the six categories on a resume (education, experience, hobbies, skills, references, contacts).
  - Likelihood of inviting for an interview.

Effects of name on reading of resume and invitation for a job interview

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	**Invitation for a job interview**		**Opening applicant's resume**		**Acquiring more information about qualification**		**Acquiring more information about other characteristics**	
Sample:	All		All		Employers who open applicant's resume			
Ethnic minority name	-0.09***		-0.08		-0.07		-0.01	
	(0.04)		(0.06)		(0.06)		(0.064)	
Asian minority name		-0.08**		-0.16**		-0.10*		0.00
		(0.03)		(0.07)		(0.05)		(0.08)
Roma minority name		-0.06*		0.03		-0.03		-0.02
		(0.03)		(0.08)		(0.06)		(0.07)
Mean of dep. var.	$\boxed{0.09}$	0.09	0.58	0.58	0.13	0.13	0.18	0.18
Observations	274	274	274	274	160	160	160	160

Only small share of applicants are invited for job interview

Effects of name on reading of resume and invitation for a job interview

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	**Invitation for a job interview**		**Opening applicant's resume**		**Acquiring more information about qualification**		**Acquiring more information about other characteristics**	
Sample:	All		All		Employers who open applicant's resume			
Ethnic minority name	$\boxed{\begin{matrix}\text{-0.09***}\\ \text{(0.04)}\end{matrix}}$		-0.08 (0.06)		-0.07 (0.06)		-0.01 (0.064)	
Asian minority name		-0.08** (0.03)		-0.16** (0.07)		-0.10* (0.05)		0.00 (0.08)
Roma minority name		-0.06* (0.03)		0.03 (0.08)		-0.03 (0.06)		-0.02 (0.07)
Mean of dep. var.	0.09	0.09	0.58	0.58	0.13	0.13	0.18	0.18
Observations	274	274	274	274	160	160	160	160

Minority names reduce the likelihood of invitation

Effects of name on reading of resume and invitation for a job interview

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	**Invitation for a job interview**		**Opening applicant's resume**		**Acquiring more information about qualification**		**Acquiring more information about other characteristics**	
Sample:	All		All		Employers who open applicant's resume			
Ethnic minority name	-0.09***		-0.08		-0.07		-0.01	
	(0.04)		(0.06)		(0.06)		(0.064)	
Asian minority name		-0.08**		-0.16**		-0.10*		0.00
		(0.03)		(0.07)		(0.05)		(0.08)
Roma minority name		-0.06*		0.03		-0.03		-0.02
		(0.03)		(0.08)		(0.06)		(0.07)
Mean of dep. var.	0.09	0.09	0.58	0.58	0.13	0.13	0.18	0.18
Observations	274	274	274	274	160	160	160	160

Asian name reduces the likelihood of reading resume

Effects of name on reading of resume and invitation for a job interview

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	**Invitation for a job interview**		**Opening applicant's resume**		**Acquiring more information about qualification**		**Acquiring more information about other characteristics**	
Sample:	All		All		Employers who open applicant's resume			
Ethnic minority name	-0.09***		-0.08		-0.07		-0.01	
	(0.04)		(0.06)		(0.06)		(0.064)	
Asian minority name		-0.08**		-0.16**		-0.10*		0.00
		(0.03)		(0.07)		(0.05)		(0.08)
Roma minority name		-0.06*		0.03		-0.03		-0.02
		(0.03)		(0.08)		(0.06)		(0.07)
Mean of dep. var.	0.09	0.09	0.58	0.58	0.13	0.13	0.18	0.18
Observations	274	274	274	274	160	160	160	160

Conditional on opening resume, qualifications of the Asian applicant are less closely inspected

Online survey among human resource managers: perceptions

Expected overall quality (q_G- d_G) higher for the majority applicant
(low expected quality for minority driven by Asian)

	White majority name (W) (1)	Ethnic minority name (E) (2)	Difference: W-E p-value (3)
Panel B: Survey among decision-makers in the labor market			
Expected applicant's overall quality	3.35	2.96	0.39 (0.02)
Standard deviation of applicant's expected overall quality	0.55	0.53	0.02 (0.84)
Expected informativeness of applicant's resume	2.97	2.62	0.34 (0.10)
Observations	29	61	

Online survey among human resource managers: perceptions

SD of applicant's expected quality (σ_G^2) the same across groups

	White majority name (W) (1)	Ethnic minority name (E) (2)	Difference: W-E p-value (3)
Panel B: Survey among decision-makers in the labor market			
Expected applicant's overall quality	3.35	2.96	0.39 (0.02)
Standard deviation of applicant's expected overall quality	0.55	0.53	0.02 (0.84)
Expected informativeness of applicant's resume	2.97	2.62	0.34 (0.10)
Observations	29	61	

Online survey among human resource managers: perceptions

Cost of information acquisition (C_1 or $\sigma^2_{G,1}$) similar for both groups

	White majority name (W) (1)	Ethnic minority name (E) (2)	Difference: W-E p-value (3)
Panel B: Survey among decision-makers in the labor market			
Expected applicant's overall quality	3.35	2.96	0.39 (0.02)
Standard deviation of applicant's expected overall quality	0.55	0.53	0.02 (0.84)
Expected informativeness of applicant's resume	$\boxed{2.97}$	$\boxed{2.62}$	0.34 (0.10)
Observations	29	61	

Existing approaches do not explain the switch (and endogeneity) in attention

- Purely taste-based discrimination (Becker 1971):
  - Attention not an issue.
- Statistical discrimination with exogenous attention:
  - Differences in priors in quality about observable group attribute (Phelps 1972, Arrow 1973)
  - Lower precision of signals from minority applicants (Cornell and Welsh 1996)
  - Information acquisition exogenous

Evidence for endogenous allocation of costly attention

- Attention discrimination predicts all of these:
  1. More attention to majority on labor market, more attention to minority on rental housing market
  2. Gap in information acquisition increases with cost of information (we show this in German experiment)
  3. Signalling recent unemployment lowers attention on labor market (we show this in German experiment)

- The switch in relative attention across markets arises if DMs:
  1. Have racist preferences ($d_{min} > d_{maj}$) (or similarly for C_2)
  2. Believe that minority candidates are of lower quality on average ($q_{min} < q_{maj}$)
  3. Expect members of a minority group to be more alike ($\sigma^2_{min} < \sigma^2_{maj}$)
- Perceptions surveys support (1) and (2), and rule out (3). We cannot distinguish between (1) and (2).

Conclusions

- Model of "attention discrimination": magnified effect of priors.
  - Prior beliefs about group affect selection decisions via Bayesian updating (standard channel) but also via the choice of attention level (new channel).
- Correspondence field experiments with monitoring information acquisition.
  - On two markets that vary in selectivity, in two countries.
  - Ethnicity-signaling names affect information acquisition, in line with model's predictions.
- The model can help explaining lower returns to higher quality resume observed in previous experiments in US (and Sweden).

Conclusions

- Policy implications:
  - Name-blind resume? Quotas for initial levels of screening?
- Measuring process-data (level of inspection) as well as outcomes (likelihood of invitation) in field experiments, using internet.

Caveats of name-blind resumes

- Although we propose blinding resumes, a note of caution has to be made: Doleac and Hansen (2018) make it by examining unintended consequences of "ban the box" (BTB) policy in the US.
- US adopted BTB preventing employers to ask about applicants' criminal history (can do so only *after* conditional offer made). Motivation:
  - Recidivism high as transition of ex-offenders to civilian lives difficult. Getting a job should lead to lower crime rates—opportunity costs (Becker 1968).
  - But Pager (2003) shows in a correspondence experiment that ex-offenders discriminated against. Assumed to be statistical. Important for BTB - why?
  - BTB advocates: once invited for interview, ex-offenders can show their job-readiness unobservable from CV.

Doleac and Hansen (2018)

- BTB does not address poor job-readiness of ex-offenders. On observables beyond "the box", ex-offenders perform relatively worse.
- What might go wrong? If criminal record unobserved, employers guess based on observables who *could have been* a criminal.
- Largest share of ex-offenders among young, low-skilled, black and Hispanic men. $\rightarrow$ employers shy away from interviewing members from these groups, regardless of their actual criminal record.
- Hypotheses:
  1. If BTB relatively increases employment for groups above: statistical discrimination not exacerbated.
  2. If BTB relatively reduces employment for the groups above: strong evidence for statistical discrimination; cost to innocent greater than benefit to ex-offenders.

Doleac and Hansen (2018): estimation strategy

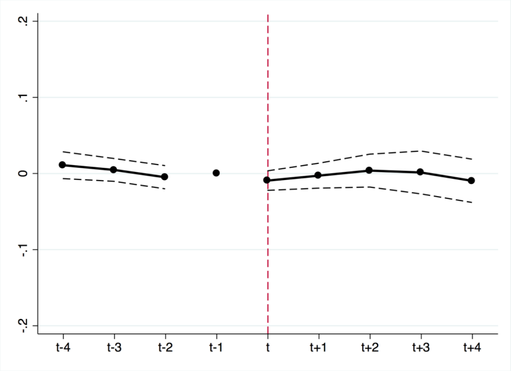
- The paper exploits a staggered introduction of this policy across states/counties/cities: 1998: Hawaii first, by 2015: 34 states (Recall Goldin and Rouse 2000).
- Individual-level data from 2004-2014 Current Population Survey (CPS): *age, sex, race, ethnicity, education level, and current employment*; 60,000 responses every month

$$\begin{aligned} Employed_i = & \alpha + \beta_1 BTB_{m,t} \times White_i + \beta_2 BTB_{m,t} \times Black_i + \\ & \beta_3 BTB_{m,t} \times Hispanic_i + \beta_4 \delta_{MSA} + \beta_5 D_i + \\ & \beta_6 \lambda_{time \times region} + \beta_7 \delta_{MSA} \times f(time)_t + \varepsilon_i \end{aligned} \tag{1}$$

- Identifying assumption: adoption of BTB policies exogenous to other labor market interventions; counterfactual: employment probabilities would evolve similarly to those in nearby non-BTB MSAs.

Doleac and Hansen (2018): results

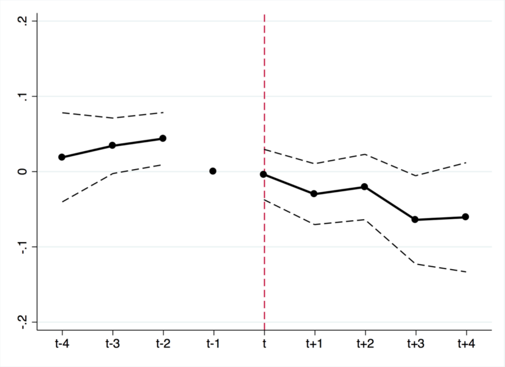
Figure 2: Effect of BTB on probability of employment for white men ages 25-34, no college degree



Data source: CPS 2004-2014. Sample includes white, non-Hispanic men ages 25-34 who do not have a college degree. The graph is a coefficient plot, showing the estimated effect of BTB in each year before and after the effective date of the policy: t-4 is four or more years before BTB, t-3 is three years before BTB, t-2 is two years before BTB, t-1 is one year before BTB, t is the effective date of the BTB policy, t+1 is one year after BTB, t+2 is two years after BTB, t+3 is three years after BTB, and t+4 is four or more years after BTB.

Doleac and Hansen (2018): results

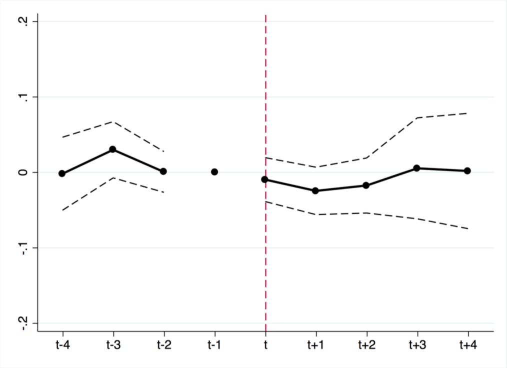
Figure 3: Effect of BTB on probability of employment for black men ages 25-34, no college degree



Data source: CPS 2004-2014. Sample includes black men ages 25-34 who do not have a college degree. The graph is a coefficient plot, showing the estimated effect of BTB in each year before and after the effective date of the policy: t-4 is four or more years before BTB, t-3 is three years before BTB, t-2 is two years before BTB, t-1 is one year before BTB, t is the effective date of the BTB policy, t+1 is one year after BTB, t+2 is two years after BTB, t+3 is three years after BTB, and t+4 is four or more years after BTB.

Doleac and Hansen (2018): results

Figure 4: Effect of BTB on probability of employment for Hispanic men ages 25-34, no college degree



Data source: CPS 2004-2014. Sample includes Hispanic men ages 25-34 who do not have a college degree. The graph is a coefficient plot, showing the estimated effect of BTB in each year before and after the effective date of the policy: t-4 is four or more years before BTB, t-3 is three years before BTB, t-2 is two years before BTB, t-1 is one year before BTB, t is the effective date of the BTB policy, t+1 is one year after BTB, t+2 is two years after BTB, t+3 is three years after BTB, and t+4 is four or more years after BTB.

More than good intentions needed

- In the full specification, BTB reduces the probability of employment:
  - For young black men without a college degree by 3.4 percentage points (5.1%)
  - For young Hispanic men without a college degree by 2.3 percentage points (2.9%).
- Similar papers:
  - Holzer et al. (2006): last hire was 37% more likely to be a black man when firms conducted **criminal background checks**
  - Bartik and Nelson (2016): banning **credit history checks** reduced the likelihood of finding a job by 7-16% for black job-seekers.
  - Wozniak (2015): allowing **drug testing** by employers increased employment for low-skilled black men by 7-30%.
- Take-away: be careful when taking away relevant signals away from decision-makers!

Discrimination on high skilled positions?

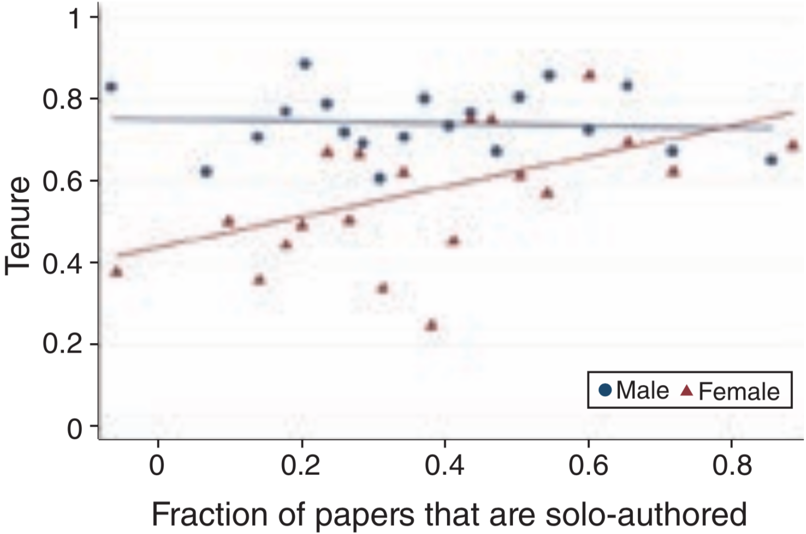
- Previous paper focuses on low skilled young men
  - Correspondence experiments: typically for mid-range positions
  - Goldin and Rouse (2000): examines 1970s and 1980s
- What about high skilled positions today? Note: low representation of women in top positions (politics, CEOs, full professors in technical fields).
- Sarsons (2017): Recognition for Group Work: Gender Differences in Academia
  - Are promotion requirements evaluated differently for men and for women in economics?
  - Data from top-30 economics department in the US.

Sarsons (2017)

- Setting: promotion in academia. Details:
  - Academics strive for tenure.
  - Committee decides mainly based on publication record whether one is worthy of receiving a tenure.
  - Publication record mostly evaluated through journal rankings.
  - Problem:
    - Papers often co-authored. Not clear who did what share of work? (In economics: alphabetic listing of authors)
    - Single-authored papers send clear signals

  Results:
  - Men and women who solo-author most of their work have similar tenure rates (conditional on paper quality).
  - Additional co-authored paper correlated with an 8 percentage point increase in tenure probability for men but only a 2 percentage point increase for women.
    - Gap is less pronounced for women who coauthor with women.
  - No gap in sociology where individual contribution signalled by ordering of authors on papers.

Sarsons (2017): results



Sarsons (2017): results

TABLE 2—RELATIONSHIP BETWEEN PAPERS AND TENURE

	Dep var: Tenure (1)	
		× Female
Solo-authored pubs	0.068	0.005
	(0.009)	(0.015)
Pubs with only male CAs	0.072	−0.071
	(0.012)	(0.019)
Pubs with male and female CAs	0.096	−0.051
	(0.033)	(0.037)
Pubs with only female CAs	0.069	0.012
	(0.016)	(0.027)
Total coauthors	−0.001	
	(0.006)	
School fixed effects	Yes	
Tenure year fixed effects	Yes	
Field fixed effects	Yes	
Observations	559	

Notes: This table presents the results of one regression where the interaction terms are displayed in the right-hand column. The regression controls for average journal quality and log citations. The equation is estimated using a probit model. The marginal probabilities calculated at the mean are displayed. Standard errors, reported in parentheses, are clustered by tenure institution.

TABLE 3—NONALPHABETICAL ORDERING: SOCIOLOGY

	(1)	
		× Female
Fraction first author	0.403	−0.042
	(0.043)	(0.172)
Solo papers	0.000	0.007
	(0.006)	(0.011)
Total coauthored	0.009	0.001
	(0.007)	(0.015)
School fixed effects	Yes	Yes
Tenure year fixed effects	Yes	Yes
Observations	237	209

Notes: This table shows the relationship between paper types and tenure for the sociology sample. The dependent variable is a binary variable indicating whether an individual received tenure six to eight years after being hired. Fraction first author is the fraction of papers an individual has on which they were first author by the time he or she went up for tenure. All regressions control for the number of books published, time to tenure, and include tenure institution and tenure year fixed effects. The equation is estimated using a probit model. The marginal probabilities calculated at the mean are displayed. Standard errors, reported in parentheses, are clustered by tenure institution.

Employers not all to blame (they are human, too)

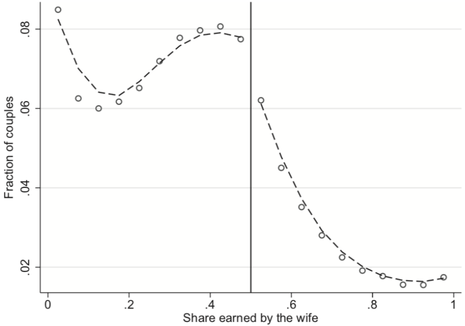


FIGURE I

Distribution of Relative Income (SIPP Administrative Data)

The data are from the 1990 to 2004 SIPP/SSA/IRS gold standard files. The sample includes married couples where both the husband and wife earn positive income and are between 18 and 65 years of age. For each couple, we use the observation from the first year that the couple is in the panel. Each dot is the fraction of couples in a 0.05 relative income bin. The vertical line indicates the relative income share = 0.5. The dashed line is the lowess smoother applied to the distribution allowing for a break at 0.5.

Source: Bertrand, Kamenica, Pan (2015)

Bertrand, Kamenica, Pan (2015)

- Standard marriage-market models in economics cannot account for this discontinuity around the threshold when wife starts earning more than a husband.
- Role of social norms?
  - World Values Survey: "If a woman earns more money than her husband, it's almost certain to cause problems."
    - 28% of couples where both have some college education agree $\rightarrow$ distribution drop at discontinuity of 5.53%
    - 45% of couples where neither has more than high-school degree agree $\rightarrow$ distribution drop at discontinuity of 20.1%
  - Norms can change: Beaman, Chattopadhayay, Duflo, Pande, and Topalova (2009): Temporary quotas for women leaders in local council change female representation after quotas discontinued.
- Take-away: start from fighting discrimination at our homes & heads!

A little experiment

- I would like you to take a short test.
    1. Go to: https://implicit.harvard.edu/implicit/takeatest.html
    2. Read the text
    3. Run a Race IAT
    4. Record your score for your reference.
    5. You have about 15 minutes to do this.

Back to IAT

- When starting to fight discrimination in our heads, remember the IAT.
- Chugh, Bertrand, and Mullainathan (2005) propose "implicit discrimination". Sometimes we do not even have to be aware of our discriminative behavior.
- Instant-decision studies show substantial discriminative behavior:
  - Basketball: NBA referees call more personal fouls against players when they are officiated by an opposite-race refereeing crew than when officiated by an own-race crew. This affects who wins. (Price and Wolfers 2007)
  - Similar evidence for baseball; when computerized systems employed, differential treatment disappears (Parsons, Sulaeman, Yates, and Hamermesh 2008)
  - Correl et al. (2002): "police officer's dilemma" (quick decisions shoot/not when shown pictures of armed/unarmed white/black men): http://psych.colorado.edu/ jclab/FPST.html

Thank you for your attention & for staying till late.

Your comments and suggestions are more than welcome at
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