Linked Out? A Field Experiment on Discrimination in Job Network Formation

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Motivation

Job networks substantially affect labor market outcomes (Schmutte, 2015; Dustmann et al., 2016)

- "half of all jobs are found through informal contacts" (Topa, 2011)
- bigger + less dense networks $\rightarrow$ frequent exposure to valuable information (Burt, 1992)
- online networks, in particular, LinkedIn, lead to jobs (Wheeler et al., 2022; Utz, 2016)
- 50% of recruitment professionals use LinkedIn to search for applicants (Caers and Castelyns, 2011)

Nevertheless, we know very little about discrimination in job network formation:
Might be part of the explanation for why minorities perform worse in the labor market:

- white male networks provide most job leads (McDonald, 2011)
- minorities strongly utilize networks – but they have 'wrong' ones

  (Fernandez and Fernandez-Mateo, 2006)

additional literature: (online) networks | additional literature: correspondence studies | additional literature: theory | definition: discrimination

This Paper

We unveil the causal role of discrimination in the job network formation and information provision of minorities

We run a large-scale two-stage field experiment on LinkedIn

- We develop networks for 400+ fake profiles by sending requests to 20k+ users
- In the **first stage**, each user is connected by a Black and a White profiles – manipulated through AI-generated pictures
- In the **second stage**, we ask contacts for job-application-relevant information

We measure differences in size, quality, and information provision of networks and provide evidence on who discriminates

Preview of Findings

We observe a substantial racial gap in the resulting networks

- In the **first stage**: Black profiles have fewer connections
- In the **second stage**: Black profiles receive fewer informational benefits
  - mainly driven by the first stage $\Rightarrow$ gatekeeping
- We find multiple relevant predictors of discrimination:
  - $\uparrow$ females
  - $\uparrow$ young users
  - $\downarrow$ Black users
- We survey experts and show that they do not anticipate our results

Contribution

Correspondence Studies
Bertrand and Mullainathan (2004), Edelman et al. (2017), Bohren et al. (2019), Acquisti and Fong (2020) ...

- signaling race via names is noisy and conveys additional information, like socioeconomic background (Fryer Jr and Levitt, 2004; Gaddis, 2017; Abel and Burger, 2023; Kreisman and Smith, 2023)

⇒ we signal race through (A.I.-generated) pictures [+] study on job networks & in low-cost setting

Predictors of Discriminatory Behavior
Ewens et al. (2014), Edelman et al. (2017), Block et al. (2021), Kline et al. (2022)

- limited empirical evidence on who drives discrimination

⇒ rich data allows us to analyze which individual characteristics are associated with discriminatory behavior

Networks and Discrimination
Arrow and Borzekowski (2004); Fernandez and Fernandez-Mateo (2006); McDonald et al. (2009)...

- little empirical evidence on the role of discrimination/homophily in job network formation

⇒ we are the first to study the role of discrimination on job network formation causally

Social Tie Formation
Marmaros and Sacerdote (2006), Mayer and Puller (2008), Cullen and Perez-Truglia (2023), Michelman et al. (2021) ...

⇒ different context: ties on LinkedIn are 'weak' and have a different objective (Gee et al., 2017; Rajkumar et al., 2022)

Roadmap of Talk

Stage I: Our General Approach

Profiles

- create 408 male profiles on LinkedIn (8 per state's biggest city) ‣ geography ‣ Ethics
- vary race: Black/White – using A.I.-generated pictures
- vary profile quality: better and worse university attended ‣ Validation: Unis

Target Profiles and Procedure

- collect the first 150 suggestions for each plain profile ‣ Locations
- create a balanced target sample for each profile ($\approx$ 50-50 gender, 70-30 race), based on name and picture
- contact 12 targets per profile each week for 8 weeks ($\approx$ 100 per profile)
- scrape targets' CVs and link them to public data

Signaling Race: Pictures

In comparison to existing studies, race is signaled through profile pictures

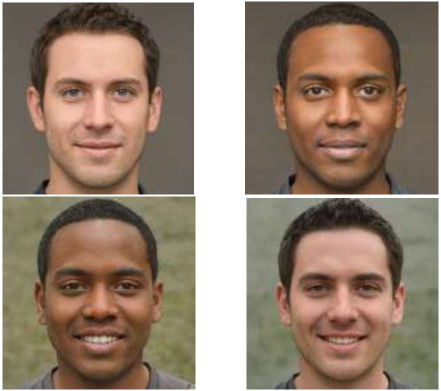
- A.I.-generated pictures are taken as inputs to create White and Black images

- our algorithm varies racial features while keeping pictures' characteristics stable (emotions, posture, age, gender, facial features, background, etc.)

▸ Documentation: Pictures

Signaling Race: Pictures

[Original (AI)] [Transformed]



In comparison to existing studies, race is signaled through profile pictures

- A.I.-generated pictures are taken as inputs to create White and Black images
- our algorithm varies racial features while keeping pictures' characteristics stable (emotions, posture, age, gender, facial features, background, etc.)

▸ Documentation: Pictures

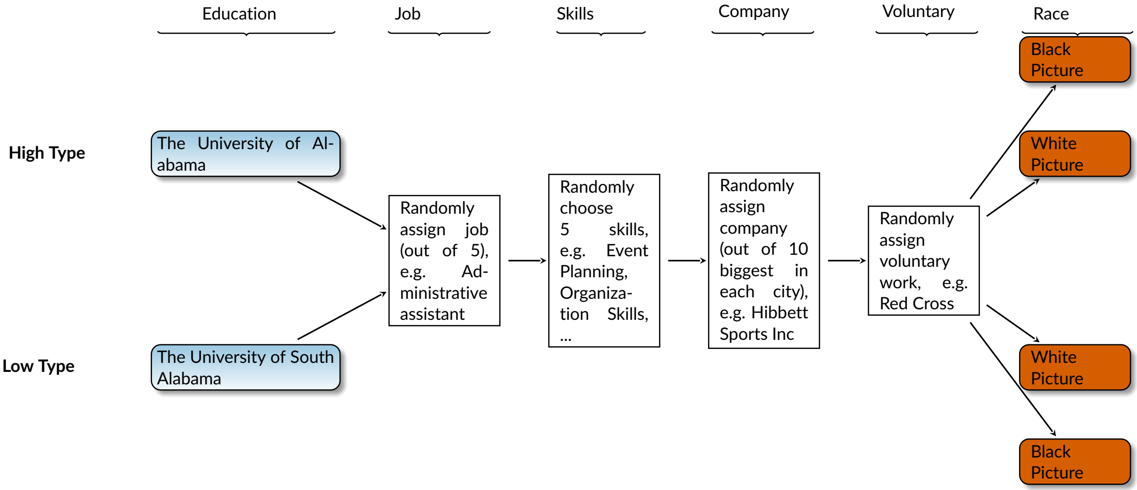
▸ Validation Experiment: Pictures are considered real

▸ Validation Experiment: Race is clearly identified

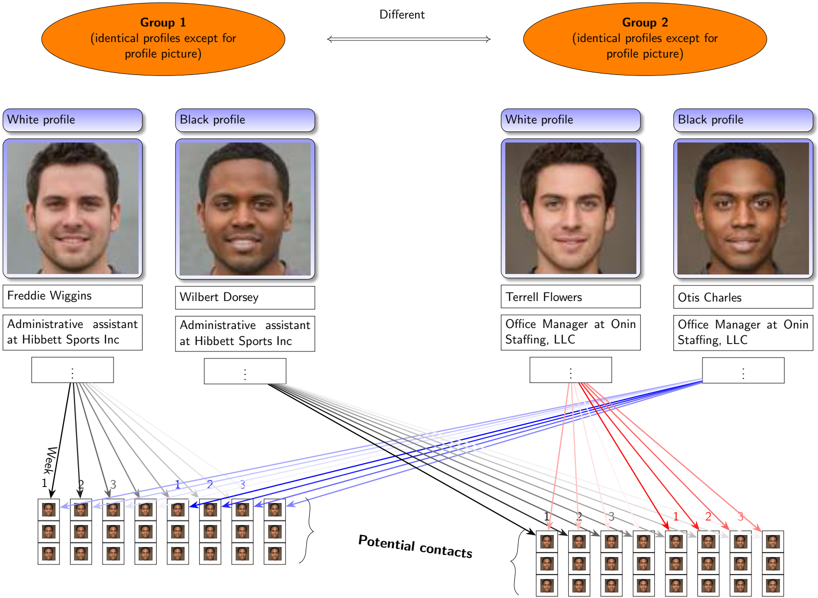
▸ Validation Experiment: Pictures of Black and White profiles are comparable

All profiles are males, born roughly 1999 (23 years) +
First and last names are equally common among Black and White people

Example: Birmingham / Alabama — Creation of high and low quality profiles: Born ∼1999



Example: Birmingham / Alabama — low quality profiles (The University of South Alabama)



Roadmap of Talk

Stage I: Results ▸ Regression

Networks:

- White profiles have 13% more connections than Black profiles (26 vs. 23)
  - 2 p.p. higher acceptance rate (Bertrand and Mullainathan, 2004; Nunley et al., 2017; Agan and Starr, 2018; Kline et al., 2022)
- No difference between high- and low-quality profiles

Who discriminates:

- We find virtually no group of users that do not discriminate
- Discriminate less: Black users, better education, **males**, **older** users, higher income...
- discriminate more: **females**, **younger** users, republican counties...
- The pattern is visible across the US
- No evidence of dynamic effects

Roadmap of Talk

Motivation & Background

Stage I: Discrimination in Network Formation

- Design
- Result

Stage II: Differences in Informational Benefits

- Design
- Results

Conclusion

- Expert survey
- Conclusion

Stage II: Motivation

In this section, we aim to answer two questions:

- Are the weak ties our profiles develop relevant?
  - provision of useful information that helps in an application process?
- Do Black profiles receive less information?
  - is this driven by the first or second stage?

Stage II: Procedure

- Each of the remaining 400 profiles contacts up to 10 connected targets[1]
- We ask targets about the application process in their company or general career advice
- Importantly, to resolve first-stage endogeneity
  - ideally each profile would message people who *typically **would accept** a Black person* and people who *typically **would not accept** a Black person*
  - we swap the picture of half of our profiles (i.e., 100 Black profiles upload the picture of their White-twin and vice versa)

▸ Not detected: Views ▸ Suspensions ▸ Responses

[1] Restriction to those who have a first name, work in a different company, are not retired, are not a freelancer, are working in a company with less than 50 employees, have not sent a message to our profiles

The usefulness of networks

▸ More Messages ▸ Summary Stats ▸ Who responds

- 20.9% responded
- Most responses are very useful (from phone calls, referrals, and references, to long messages)

Examples

*[...] I'd make sure your resume includes all the softwares/programs you've used[...]**I'm happy to submit you in as a referral if you like.** This will help get you to the front of the line for applicants.*

*Thanks for reaching out. I would connect with Tiffany McDougal and **feel free to mention my name**. [...]*

*[...] some common skills and experiences that we look for are: organized, proactive, taking initiative, experience with systems like outlook, workday, and zoom, [...][...] If you're interested in a role supporting our field and store teams, we have some movement on our admin team in my region, and **I'd be happy to pass your resume along to our recruiter.** [...]*

Stage II: Results

- No difference in **responses** to messages between Black and White profiles
- Smaller networks $\Longrightarrow$ smaller number of **expected responses** $\Longrightarrow$ less information
  - the result is driven by the first stage $\Longrightarrow$ gatekeeping

Expert survey ▸ Details ▸ Results

- How do our results correspond to the a priori beliefs of academic economists?
- We asked $>$2000 labor economists to predict the results of our study (NBER SI Labor '21, '22 & IZA Network)
- $>$250 experts responded
- We find that experts...
  - .. correctly predict the first stage
  - .. contrary to findings, expect similar levels of discrimination during the second stage
  - .. expect males and old people discriminate more – we find the opposite
- $\Rightarrow$ highlights the need to better understand *who* discriminates in order to design effective policies targeting discrimination

Conclusion

- We conduct a large-scale two-stage field experiment on LinkedIn
- We manipulate race through A.I.-generated pictures
- The results show that White profiles..
  - .. have about 13% more contacts than Black profiles
  - .. receive more information, driven primary by more contacts
- We find multiple predictors of discrimination: gender, age, race, and location
- Back-of-the-envelope calculations show that the discrimination of Black profiles is associated with a monthly cost of $\approx$ \$200 calcs
- In summary, we unveil a mechanism of discrimination, which might be able to explain some of the labor market differences between Black and White people

Thank you for your attention!

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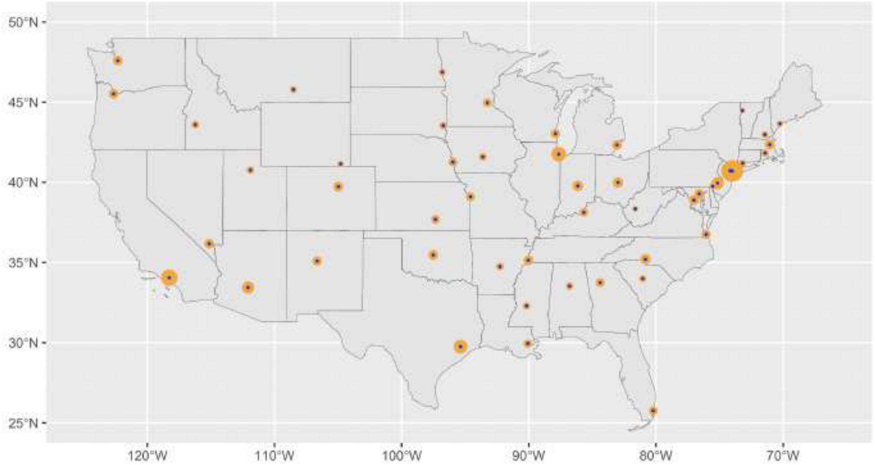
Geography

Cities: Biggest city (by population) in each federal state



▸ back

Defining Discrimination

Bertrand and Duflo (2017):"Members of a minority group (women, Blacks, Muslims, immigrants, etc.) are treated differentially (less favorably) than members of a majority group with otherwise identical characteristics in similar circumstances."

types of discrimination:

- taste-based: distaste for interacting with / hiring / rewarding /... members of a certain minority group (Becker, 1957)
- statistical: because of imperfect information and differences in the priors for certain groups, groups are treated differently (Phelps, 1972)

back

Ethics I/III

▸ Back

Salganik (2019) suggest considering the following when running field experiments on discrimination:

1. Limit harm to participants
   - answering to connection requests takes seconds
   - answering a message takes a bit longer, but, overall, low costs compared to usual correspondence studies
2. evaluate costs against "the great social benefit of having a reliable measure of discrimination"
   - first experiment on discrimination in job network formation $\rightarrow$ half of jobs are found through job networks
3. "the weakness of other methods of measuring discrimination"
   - we are not aware of any causal study on discrimination in job network formation

Ethics II/III

Other considerations

- Deception, as inherent in most correspondence studies (Bertrand and Duflo, 2017). Nevertheless, some points:
  - unlikely that 20k requests reduce the internal validity of future studies on a platform with 900 mln users. Also: subjects not usually used for economic studies
  - on a platform with many fake accounts (though probably less than on others), users expect some level of deception
  - in the context of correspondence studies, both previous research and lawmakers have acknowledged the need for deception, as informing participants would invalidate the results (Zschirnt, 2019)
- Debriefing: we only debrief those that answer our messages with a thank you message
  - debriefing with details on study might have imposed costs on participants
  - those that do not accept could anyway (usually) not be contacted
- Costs on others: compared to usual correspondence studies, our treatment has no costs on third parties (i.e. other users)

Ethics III / III

Pictures: We have carefully considered their use, especially given recent controversies around apps like *FaceApp*

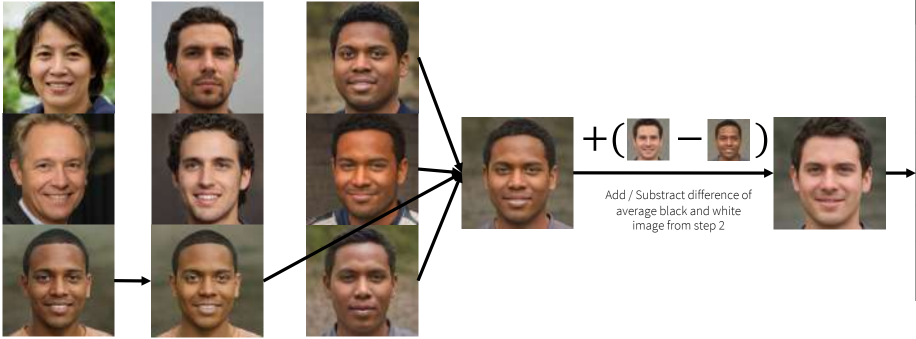
- our algorithm is agnostic in the sense that we do not make any choices as to what constitutes the features of Black or White individuals
- none of the pictures we use are of real human beings
- we swap pictures in both directions
- the algorithm is not used for entertainment purposes but merely for scientific reasons

  $\rightarrow$ Given the issues of previous studies, it can strongly improve the measure of discrimination, especially in online contexts

Platform: platforms have become a vital part of the public sphere. We follow previous researchers and courts in the argument that these must be subject to public scrutiny and enable researchers to conduct independent studies on the respective platforms. We are not aware of *any independent* published studies on LinkedIn

Picture Documentation

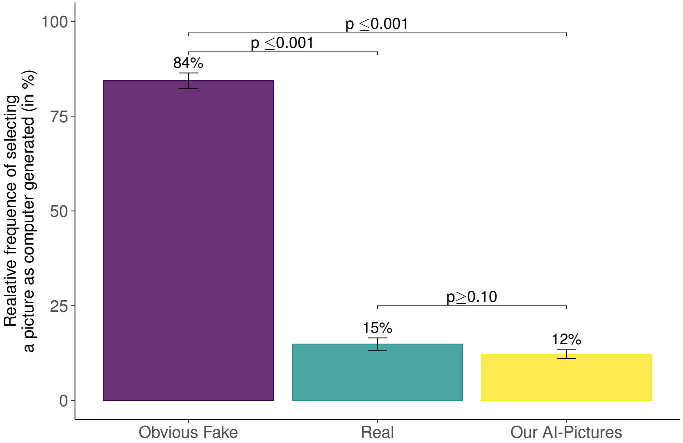
Input images	1. Automatic sorting	2. Manually check images	3. Create 'grandchildren'	4. Difference Vector	5. Translate images from black to white et vice versa	6. Verify picture characteristics using deepface	7. Verify pictu characteristics or
100k images created by StyleGAN2 and	Use deepface to sort through pictures Choose target images by age, gender, ethnicity	Manually go through black images to remove misclassifications. Pick a similar number of white pictures. Translate images into vector space.	Create grandchildren of any 4 images that, at most, share two grandparents	Use original input images to create transformation algorithm			
	Result: > 10k white images ~200 black images	Result: 42 black images 51 white images	Result: 2,310 black images 2,310 white images	Transformation Vector	Result: 2,310 transformed black and white images	Result: Pre-selection of 764 images for further analysis	Result: Final picture



	Black image	White image
age	25	26
gender	m	m
black	76.95	0
white	0.15	99.88
disgust	0	0
fear	0.07	0
⋮	⋮	⋮

back

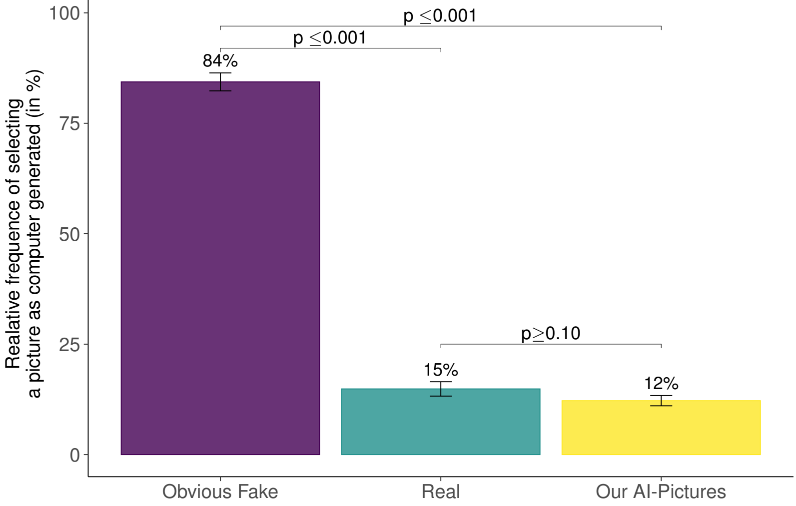
Pictures are Considered Real ‣ Screenshot ‣ Study details



Pictures are comparable across other characteristics (age, trust, looks, authenticity, intelligence) ‣ see

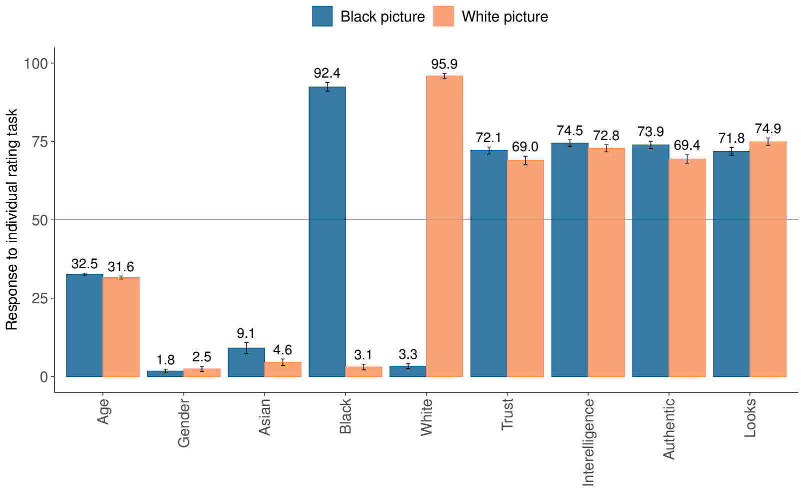
Validation I

▸ Back ▸ Screenshot ▸ Study details



Validation II

▸ Back ▸ Screenshot ▸ Screenshot(Obvious fake) ▸ Study details



Pretest Experiment
Back

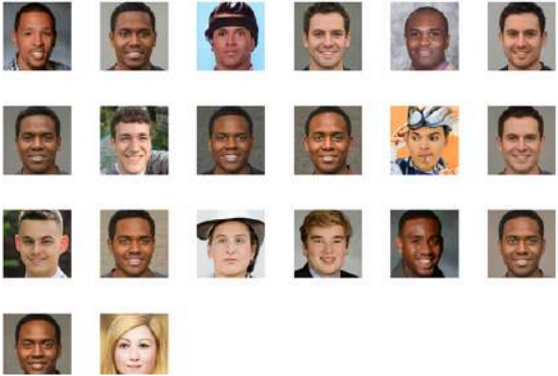
- We run a validation experiment on Mturk with 507 participants
- The experiment consisted of:
  - Demographics
  - Incentivized Captcha to measure whether profiles are considered fake
  - Evaluation of 11 A.I. created pictures (one was obvious fake with a hat)
  - Evaluation of good and bad universities in each state

Screenshot (Captcha) ‣ Back

In this simple task you are asked to select all the pictures which are computer generated (i.e. created by an artificial intelligence (AI)).

Please select any pictures you believe are created by a computer program.

If you correctly choose all pictures created by a computer program you will receive a bonus payment of 20 cents.



Screenshot (Individual)

Back

Picture #1 out of 11

In this task you are asked to judge the pictures below with regard to the following questions:

How old is the person in this picture?

14 (years old) — 99 (years old)

How likely is the person a female?

0 (not at all likely) — 100 (very likely)

How likely is the person in this picture Asian?

0 (not at all likely) — 100 (very likely)

How likely is the person in this picture African American?

0 (not at all likely) — 100 (very likely)

How likely is the person in this picture white?

Screenshot (Obvious Fake)

Back

Picture #6 out of 11

In this task you are asked to judge the pictures below with regard to the following questions:

	How old is the person in this picture?	
14 (years old)		99 (years old)

	How likely is the person a female?	
0 (not at all likely)		100 (very likely)

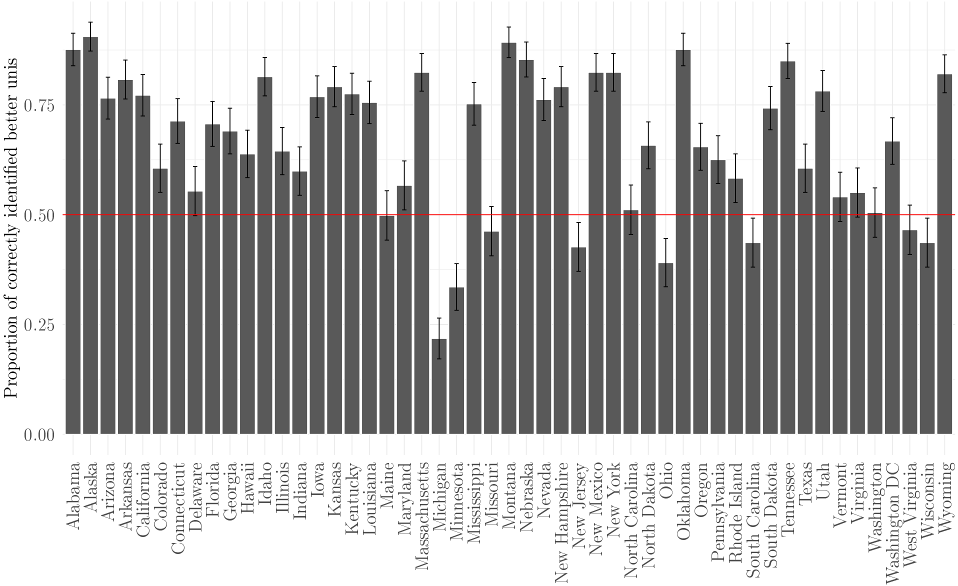
	How likely is the person in this picture Asian?	
0 (not at all likely)		100 (very likely)

	How likely is the person in this picture African American?	
0 (not at all likely)		100 (very likely)

	How likely is the person in this picture white?	
0 (not at all likely)		100 (very likely)

Validation Unis

‣ back ‣ Screnshot



Screenshot (Unis) Back

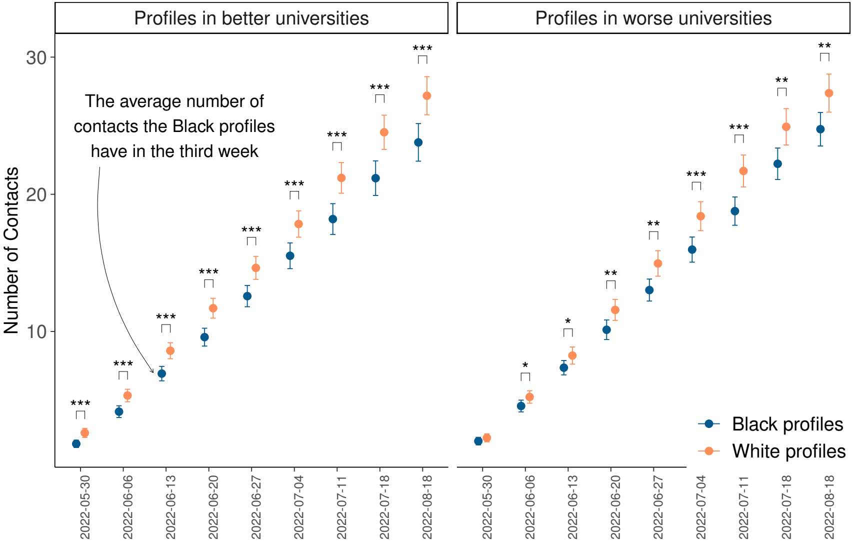
In this simple task you are asked to select the better ranked university

Below you see two universites for some of the US states. Please select the university you think is better ranked for each state out of the two options shown.
For each correct choice, you will receive 1 cent.

State	Options	
Alabama	University of North Alabama	The University of Alabama
Washington	Peninsula College	Washington State University
Arizona	Arizona State University	University of Phoenix - Arizona
Arkansas	University of Central Akransas	University of Arkansas
California	Dominican University of California	University of San Diego
Colorado	University of Denver	University of Northern Colorado

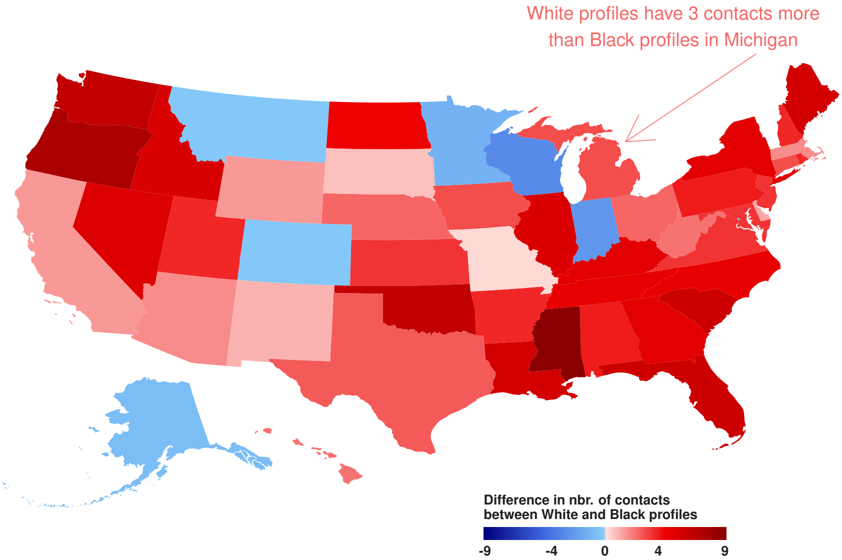
Difference in contacts over time

▸ Dynamics ▸ Back



Difference in contacts over space

▸ Reg ▸ Back



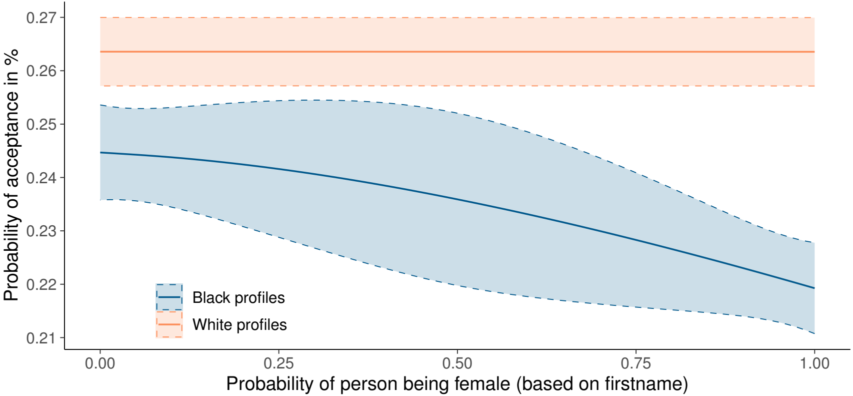
▸ State-Level Regressions

State-level regressions ‣ back

	Difference in the number of contacts											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Constant	2.89***	2.93***	2.82***	4.23*	2.33***	4.79**	4.62***	4.62***	2.44***	3.19***	2.99***	2.46***
	(0.47)	(0.47)	(0.53)	(1.70)	(0.51)	(1.47)	(1.00)	(1.00)	(0.44)	(0.38)	(0.38)	(0.37)
Absolute Male	0.0000											
	(0.0000)											
Edu: Share Bachelor		0.0000										
		(0.0000)										
Absolute White			0.0000									
			(0.0000)									
Share White				−1.79								
				(2.45)								
Share African-American					6.26$^{\cdot}$							
					(3.45)							
Share Democratic						−3.64						
						(2.95)						
GDP per Capita (current USD)							−0.0000$^{\cdot}$	−0.0000$^{\cdot}$				
							(0.0000)	(0.0000)				
In Bible Belt									1.46*			
									(0.70)			
In Rust Belt										−1.12		
										(0.96)		
In Mormon Belt											0.22	
											(1.10)	
In Black Belt												2.35**
												(0.77)
Observations	51	51	51	51	51	51	51	51	51	51	51	51

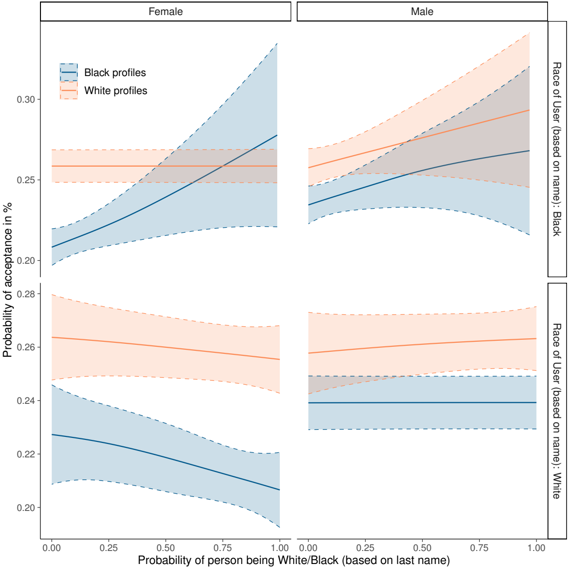
Notes: $^{\cdot}p<0.10$; $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Predictor of discrimination: Gender ‣ Back



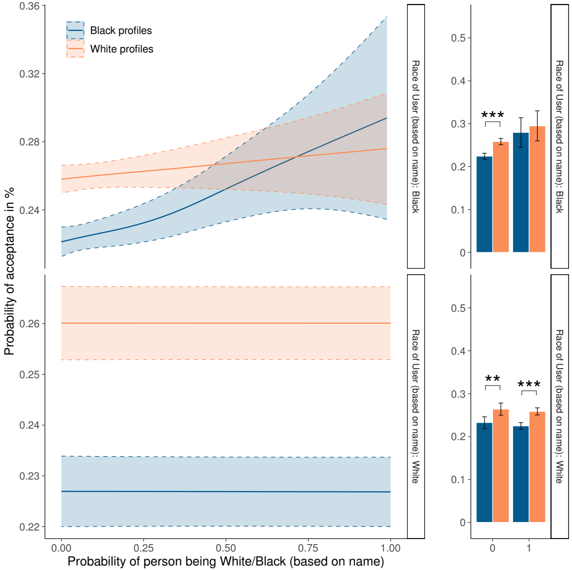
Predictor of discrimination: Gender & Race

Back



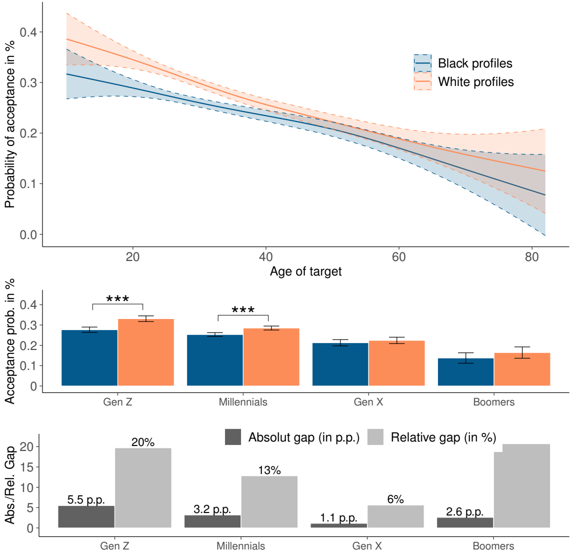
Predictor of discrimination: Race

Back

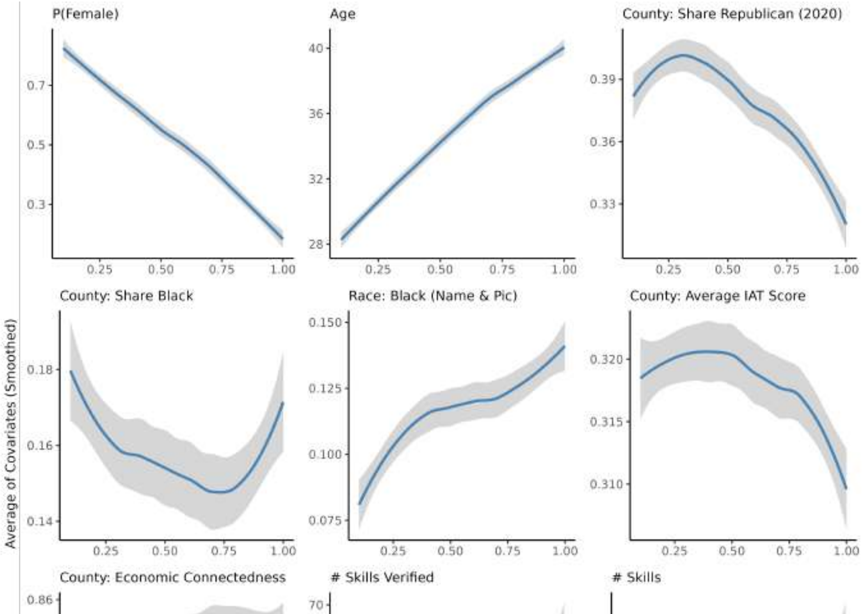


Predictor of discrimination: Age

Back

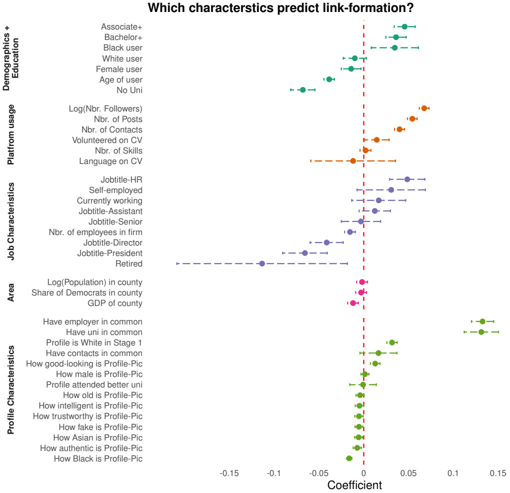


Predictor of discrimination: CATE ▸ Back



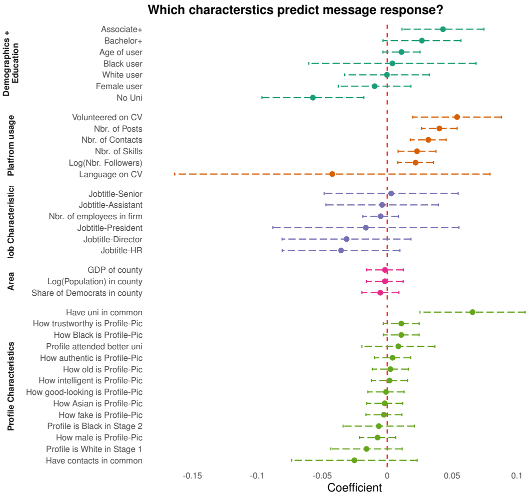
Predictors of acceptance

Back



Predictors of response

Back



Regression on number of contacts ▸ Back

Panel B: Differences in number of contacts accounting for profile quality

	Number of Contacts					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	22.79***	35.93***	22.58***	22.51***	21.66***	35.25***
	(0.63)	(1.95)	(1.17)	(1.00)	(1.23)	(2.45)
Profile is White	3.26***	3.27***	3.26***	3.54***	3.24***	3.57***
	(0.68)	(0.67)	(0.68)	(0.67)	(0.70)	(0.69)
Profile attented worse Uni	0.56	0.58	0.57	0.72	0.38	0.80
	(0.88)	(0.72)	(0.89)	(0.88)	(0.91)	(0.74)
Profile is White and attented worse Uni	−0.40	−0.42	−0.40	−0.79	−0.36	−0.85
	(0.95)	(0.95)	(0.95)	(0.94)	(0.98)	(0.96)
State Controls	×	✓	×	×	×	✓
Job Controls	×	×	✓	×	×	✓
Firstname Controls	×	×	×	✓	×	✓
Lastname Controls	×	×	×	×	✓	✓
Picture specific random effects	✓	✓	✓	✓	✓	✓
Log Likelihood	-1277.43	-1106.6	-1273.36	-1258.89	-1253.32	-1062.41
Observations	400	400	400	400	400	400

Notes: $^{\cdot}p<0.10; ^{*}p<0.05; ^{**}p<0.01; ^{***}p<0.001$

Regression on predictors of discrimination

Back

	Accepted contact request									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Constant	0.25*** (0.005)	0.28*** (0.01)	0.25*** (0.004)	0.35*** (0.01)	0.28*** (0.005)	0.25*** (0.004)	0.20*** (0.01)	0.24*** (0.004)	0.26*** (0.01)	0.27*** (0.01)
Profile is White	0.04*** (0.004)	0.02*** (0.004)	0.04*** (0.004)	0.07*** (0.01)	0.05*** (0.005)	0.03*** (0.003)	0.04*** (0.01)	0.04*** (0.004)	0.02*** (0.01)	0.05*** (0.01)
I(gender_firstname != "female")	0.03*** (0.01)									
profile_SkinWhite:I(gender_firstname != "female")	−0.02*** (0.01)									
genderprob_firstname		−0.03*** (0.01)								
profile_SkinWhite:genderprob_firstname		0.03*** (0.01)								
race_black			0.06*** (0.02)							
profile_SkinWhite:race_black			−0.04* (0.02)							
age_full				−0.003*** (0.0003)						
profile_SkinWhite:age_full				−0.001*** (0.0003)						
age_full_median					−0.05*** (0.01)					
profile_SkinWhite:age_full_median					−0.02*** (0.01)					
same_uni						0.10*** (0.01)				
profile_SkinWhite:same_uni						0.02** (0.01)				
contact_count							0.0002*** (0.0000)			
profile_SkinWhite:contact_count							−0.0000* (0.0000)			
I(contact_count == 500)								0.06*** (0.01)		
profile_SkinWhite:I(contact_count == 500)								−0.02*** (0.01)		
I(log(county_share_dem))									−0.01 (0.01)	
profile_SkinWhite:I(log(county_share_dem))									−0.02 (0.01)	
I(log(county_share_rep))										0.005 (0.01)
profile_SkinWhite:I(log(county_share_rep))										0.01** (0.01)
Picture random effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Target random effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Log Likelihood	-17504.15	-17503.42	-15942.03	-16895.43	-16911.38	-18193.72	-18029.33	-18055.41	-17296.82	-17296.72
Observations	36,911	36,911	33,861	33,446	33,446	38,299	37,154	37,154	36,306	36,306

Notes: $^{\cdot}p<0.10$; $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Some ancillary results

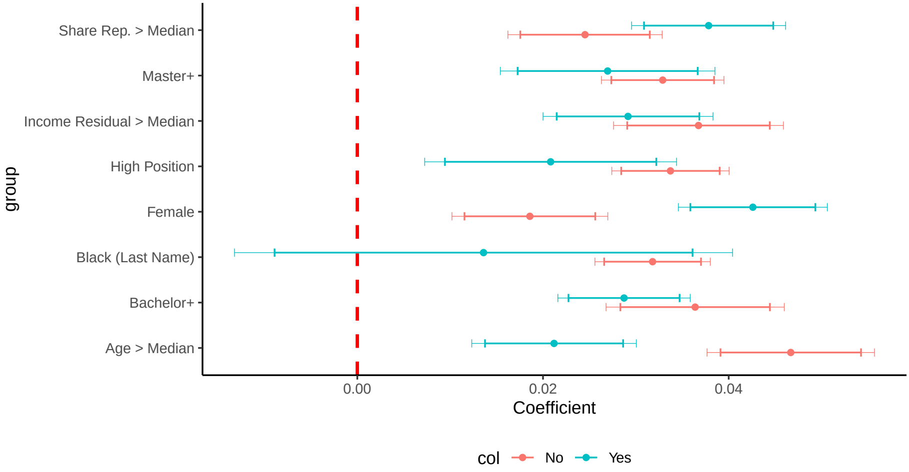
▸ Back

	Dependent variable:			
	Messages Received	Messages (non-Platform)	Num. Friend Requests	Num. Profile Views
	(1)	(2)	(3)	(4)
Profile is White	0.083	0.093*	−0.010	5.720***
	(0.071)	(0.053)	(0.129)	(0.684)
Constant	0.766***	0.214***	0.960***	35.642***
	(0.050)	(0.037)	(0.091)	(0.483)
Profile Picture FE	No	No	No	No
Observations	400	400	400	400
R^2	0.003	0.008	0.00002	0.149
Adjusted R^2	0.001	0.005	−0.002	0.147
Residual Std. Error (df = 398)	0.712	0.526	1.289	6.842

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Predictors of differences: Interaction

back



Connection Deletions: Always Accepters

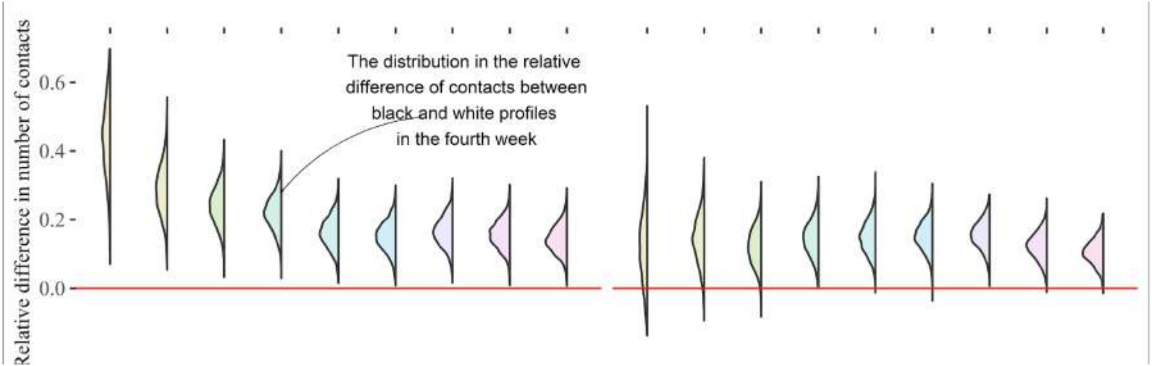
Back

Connections deleted among always-accepters

Accepted Both	Deleted Both	Deleted Only Black	Deleted Only White
3170	24	6	5

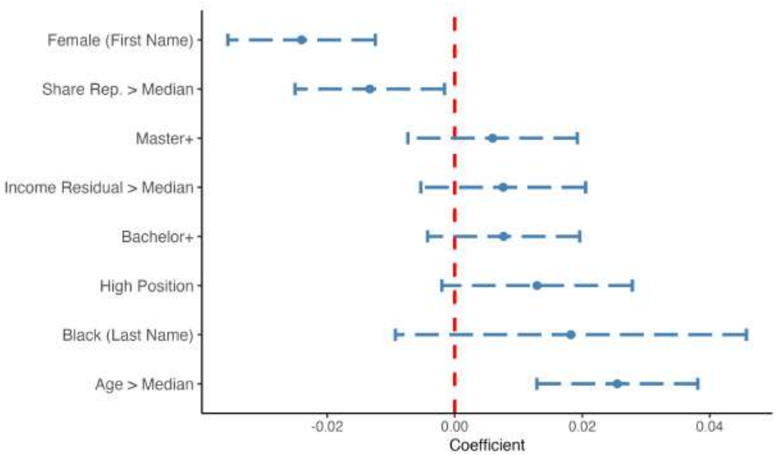
Dynamics: Relative Difference in # Contacts ‣ back

High Types — Low Types



Predictors of differences

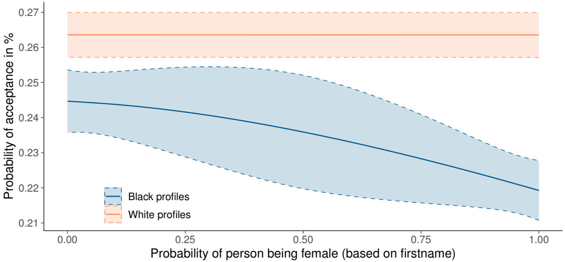
Which Characteristics Predict a Higher (Lower) Gap in White vs. Black Acceptance Rate?



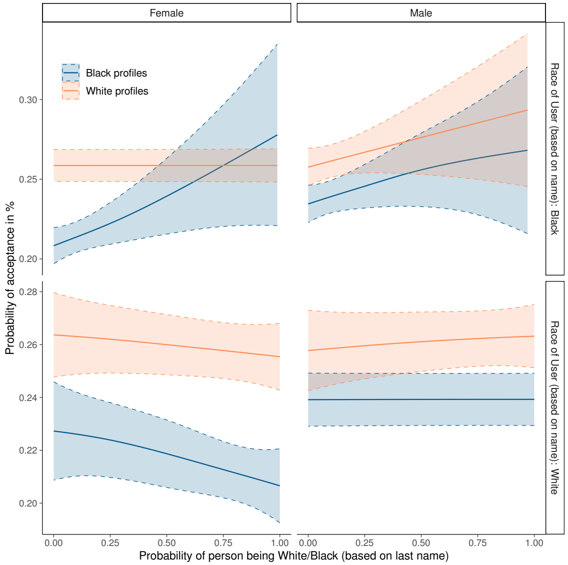
Overall: we find no variable that predicts no or positive discrimination

Exploring Differences: Female ▸ Back

- lower acceptance rate? No! females accept white profiles to the same extent as males
- omitted variables? doesn't seem so: controlling for other characteristics does not change the result
- likely explanation: dating preferences

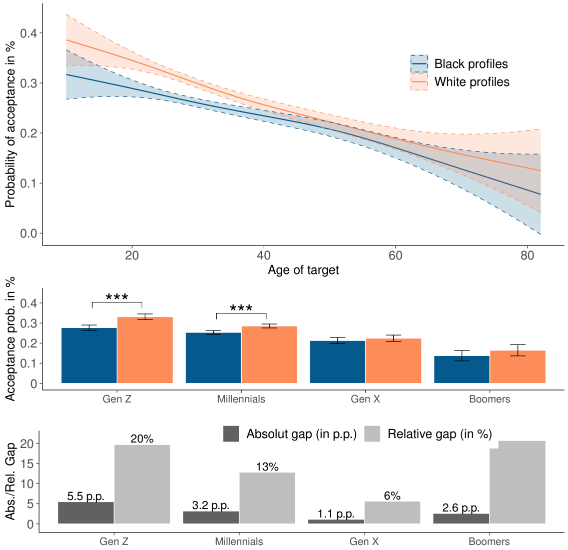


Exploring Differences: Female ▸ Back

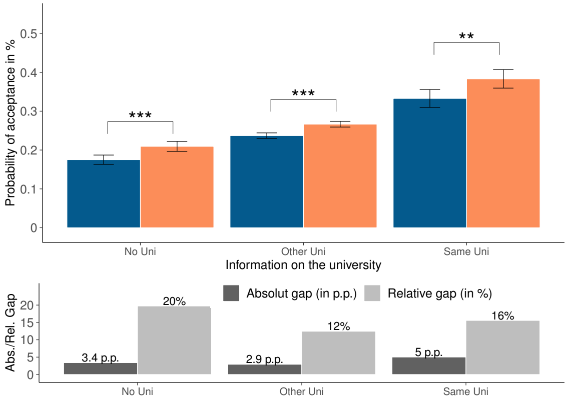


Exploring Differences: Age

Back

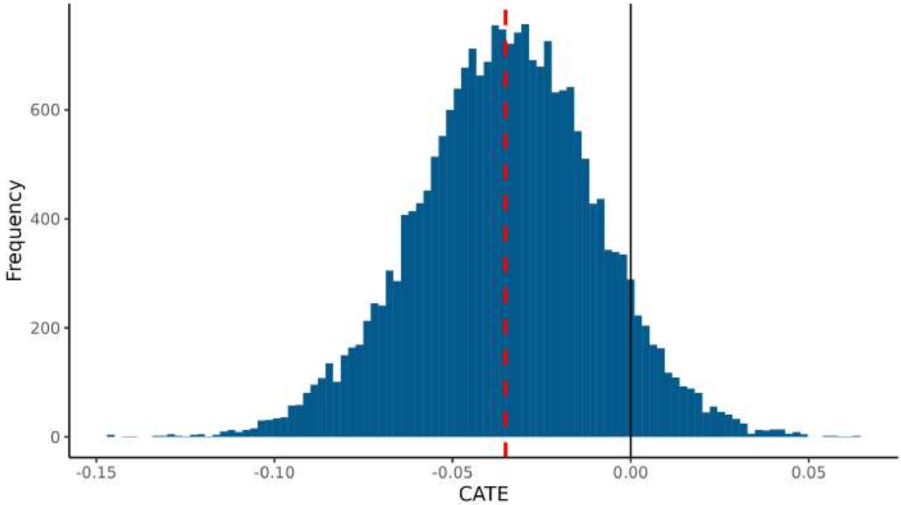


Exploring Differences: Same University ▸ Back



Conditional Average Treatment Effects

Based on Causal Forest (Wager and Athey, 2018; Athey et al., 2019)



▸ back

Response rate ▸ Back

Panel B: Differences in messages accounting for profile quality

	Response Rate					Message Length (in char)					Highly Useful Message?				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Constant	0.20***	0.36***	0.15***	0.19	0.27$^{\cdot}$	88.40***	98.81***	79.94***	39.36	30.48	0.09***	0.15$^{\cdot}$	0.02	0.09	0.11
	(0.01)	(0.06)	(0.04)	(0.12)	(0.14)	(7.23)	(25.85)	(19.21)	(59.59)	(75.73)	(0.02)	(0.08)	(0.06)	(0.19)	(0.23)
Profile is Black	0.03	0.03	0.03	0.03	0.03	−11.75	−12.27	−10.38	−13.00	−13.17	−0.02	−0.03	−0.03	−0.02	−0.04
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(9.93)	(10.33)	(10.23)	(10.09)	(10.95)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Profile attended worse Uni	0.02	0.02	0.02	0.02	0.03	−9.80	−12.76	−6.73	−9.14	−10.65	−0.02	−0.04	−0.01	−0.03	−0.04
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(9.93)	(10.30)	(10.37)	(10.34)	(11.41)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
Profile is Black and attended worse Uni	−0.07*	−0.07*	−0.07*	−0.07*	−0.07*	1.87	3.21	2.58	3.88	7.94	0.03	0.03	0.02	0.03	0.04
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(13.98)	(14.50)	(14.66)	(14.23)	(15.69)	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)
State Controls	×	✓	×	×	✓	×	✓	×	×	✓	×	✓	×	×	✓
Job Controls	×	✓	×	×	✓	×	✓	×	×	✓	×	✓	×	×	✓
Firstname Controls	×	×	✓	×	✓	×	×	✓	×	✓	×	×	✓	×	✓
Lastname Controls	×	×	✓	×	✓	×	×	✓	×	✓	×	×	✓	×	✓
Picture trait Controls	×	×	×	✓	✓	×	×	×	✓	✓	×	×	×	✓	✓
Picture specific random effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Log Likelihood	203.63	119.95	158.8	163.48	37.82	-1878.86	-1635.63	-1782.17	-1868.26	-1527.78	47.14	-11.06	6.3	10.08	-86.62
Observations	400	400	400	400	400	339	339	339	339	339	338	338	338	338	338

Notes: $^{\cdot}p<0.10$; $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Table: Response rate and message characteristics

Response rate and message characteristics by network ▸ Back

Panel A: Aggregate difference in messages (response rate, length and usefulness)

	Response Rate				Message Length (in char)				Highly Useful Message?			
	Native		Alien		Native		Alien		Native		Alien	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Constant	0.21^{***}	0.34	0.21^{***}	0.36	73.47^{***}	94.17	93.94^{***}	-155.01	0.08^{***}	-0.10	0.07^{***}	0.40
	(0.01)	(0.23)	(0.02)	(0.25)	(6.26)	(121.13)	(7.75)	(140.68)	(0.02)	(0.40)	(0.02)	(0.38)
Profile is Black	0.01	0.01	-0.02	-0.02	0.87	2.20	-22.73^{*}	-16.07	-0.002	0.001	-0.02	$-0.06^{\cdot}$
	(0.02)	(0.02)	(0.02)	(0.02)	(8.83)	(12.39)	(10.85)	(14.19)	(0.03)	(0.04)	(0.03)	(0.04)
State Controls	×	✓	×	✓	×	✓	×	✓	×	✓	×	✓
Job Controls	×	✓	×	✓	×	✓	×	✓	×	✓	×	✓
Firstname Controls	×	✓	×	✓	×	✓	×	✓	×	✓	×	✓
Lastname Controls	×	✓	×	✓	×	✓	×	✓	×	✓	×	✓
Picture trait Controls	×	✓	×	✓	×	✓	×	✓	×	✓	×	✓
Picture specific random effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Log Likelihood	113.44	-30.23	90.54	-39.88	-965.65	-586.75	-909.56	-504.49	16.51	-76.91	32.34	-65.85
Observations	200	200	200	200	177	177	162	162	176	176	162	162

Notes: $^{\cdot}p<0.10$; $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

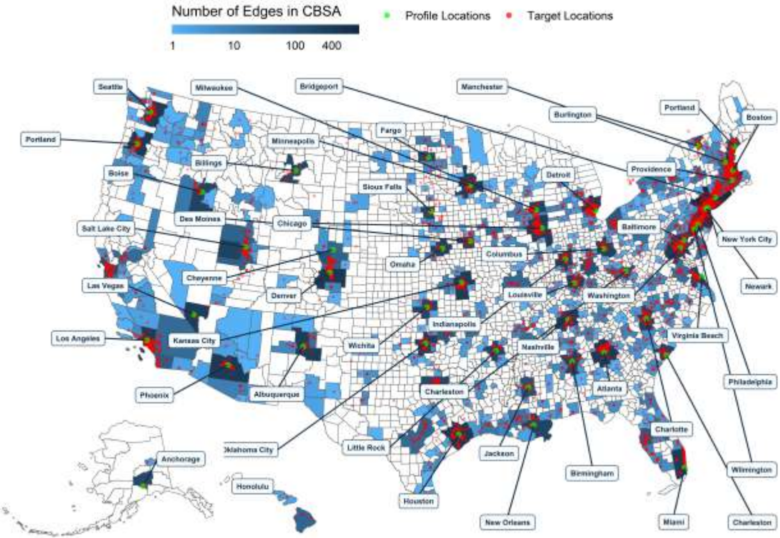
Table: Response rate and message characteristics by network

Differences in informational benefit ‣ Back

Panel B: Differences in the ex-ante informational benefit of the network accounting for profile quality

	Ex-ante informational benefit						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	4.31***	7.05***	4.29***	4.24***	4.04***	3.97***	6.57***
	(0.13)	(0.39)	(0.25)	(0.21)	(0.26)	(1.10)	(1.07)
Profile is White	0.61***	0.62***	0.61***	0.69***	0.62***	0.57***	0.65***
	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.15)	(0.15)
Profile attended worse Uni	0.07	0.08	0.08	0.11	0.05	0.06	0.11
	(0.19)	(0.15)	(0.19)	(0.19)	(0.19)	(0.19)	(0.16)
Profile is White and attended worse Uni	−0.10	−0.11	−0.10	−0.20	−0.11	−0.07	−0.22
	(0.20)	(0.20)	(0.20)	(0.19)	(0.20)	(0.20)	(0.20)
State Controls	×	✓	×	×	×	×	✓
Job Controls	×	×	✓	×	×	×	✓
Firstname Controls	×	×	×	✓	×	×	✓
Lastname Controls	×	×	×	×	✓	×	✓
Picture trait Controls	×	×	×	×	×	✓	✓
Picture specific random effects	✓	✓	✓	✓	✓	✓	✓
Log Likelihood	-660.87	-558.05	-662.8	-655.12	-658.83	-683.61	-580.49
Observations	400	400	400	400	400	400	400

Target Locations ‣ Back



The usefulness of networks ▸ Back

Examples

[...] I'd make sure your resume includes all the softwares/programs you've used, as recruiters will look for certain keywords when reviewing resumes. I'm happy to submit you in as a referral if you like. This will help get you to the front of the line for applicants. "

"Thanks for reaching out. I would connect with Tiffany McDougal and feel free to mention my name. [...]"

[...] some common skills and experiences that we look for are: organized, proactive, taking initiative, experience with systems like outlook, workday, and zoom, comfortable with reporting and learning new technology, resourceful, and building strong relationships across organizational lines. Our company values are rooted in connection, inclusivity and drive. [...] If you're interested in a role supporting our field and store teams, we have some movement on our admin team in my region, and ***I'd be happy to pass your resume along to our recruiter.*** *[...]*

"Justin, I left Wallick and Volk after nearly 13 yrs, I needed a change. Great company but just like all mortgage cos right now they are downsizing"

Summary Statistics: Message Content ▸ Back

Classification	Avg / Share
How useful is this message? (1-5)	2.49
How friendly is the message? (1-5)	3.54
Is Useful	44.33%
Offers a referral or reference	5.50%
Refers the profile to a more relevant person	5.83%
Offers to meet in person or talk on the phone	3.50%
Shares own experience	25.33%
Shares materials	7.00%
Shares useful specific advise and information	27.83%
Shares generic advise	43.50%
Engaged in conversation/ asks clarifying questions	20.33%
Offers to keep in touch	13.67%
Message did not fit recipient	22.00%
Message would harm chances of success	0.17%

Note: Summary statistics refer to the first 300/681 messages coded by two RAs.

Expert Survey details ▸ Back

- To contrast our findings to the priors of researchers working in the field, we conducted an expert survey in early June 2023.
- We send the survey to 2,143 labor economists (from Institute for Labor Economics' (IZA) network and participants in the 'NBER's Summer Institute: Labor Studies' from 2021 and 2022.)
- 269 (12.6%) experts have taken part and finished the survey.
- 27 % are female, 25% live in the US, 86% are White, 7% Asian, 3% Hispanic, 2% Middle Eastern, and 1% are Black.
- 82% have a professorial position (assistant, associate, or full professor) and 97 % have published in a peer-reviewed journal.
- 93% consider themselves labor economists, and 57 % do research on discrimination.

Expert Survey results

▸ Back

paper_v1/figure/ExpertSurveyOne_Full-1.png

Figure: Experts' predictions of discrimination on LinkedIn

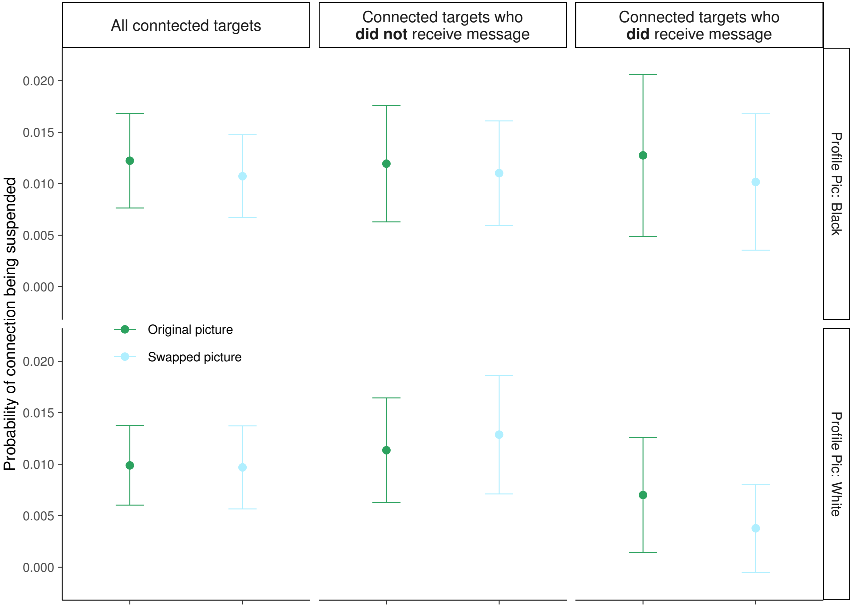
No difference in views after swapping

▸ Back

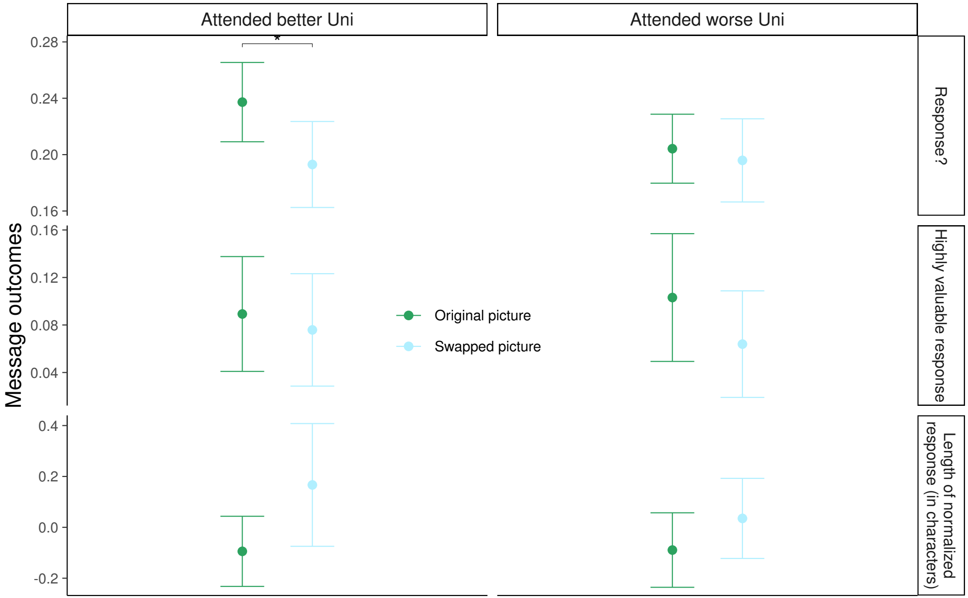
paper_v1/figure/ViewsOverTime-1.png

No difference in suspension after swapping

▸ Back



No clear difference in responses after swapping ‣ Back



Back-of-the-envelope calculation ▸ Back

Approach 1: Ties and Jobs

- Rajkumar et al. (2022): each weak tie increase prop of job by 0.0047.
- White user have 286 connections + Black users expected to have a 13% smaller network
- Annual wage of $45,000 for similar profile
- $\Rightarrow$ $2239 being "lost" by a Black user due to a smaller network.

Approach 2: Referrals and Wage

- Referrals result in an increase of the initial wage by roughly 2.5% (Dustmann et al., 2016)
- Referral probability in our setting: 0.014
- $\Rightarrow$ disparity between Black and White annual wages $\approx$ $550.

Approach 3: Contacts and Income

- Linear regression of a target's income on her number of connections
- An additional connection is associated with $70.6 additional yearly income
- White user has 286 connections + expect Black profiles to have 13% less.
- $\Rightarrow$ Wage loss of $2,612 for Black users.