Discriminatory Lending: Evidence from Bankers in the Lab

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Motivation

- In many emerging markets, far fewer women than men use financial services
- Cause?
  - Demand: Selection into small firms, less capital-intensive sectors
  - Supply: Institutional barriers and gender discrimination by banks
- Female entrepreneurs credit constrained $\rightarrow$ productive capacity underutilized $\rightarrow$ economic convergence slows

Detecting discrimination

- Administrative data: suggestive but inconclusive evidence of gender discrimination in lending
- Drawbacks of administrative data:
  1. Omitted variables bias
  2. Difficult to disentangle demand and supply
  3. Loan officer traits unobserved (exception: Beck et al. 2013; 2018)

Our contribution: Lab-in-the-field

1. Controlled setting
   - Randomize applicant gender: No omitted variables bias
   - Vary available information to understand the nature of discrimination
   - Psychometrics: Measure personality traits that are usually unobservable
2. Realistic setting
   - Population of interest: Real loan officers
   - Real applications that we can track over time (Cole, Kanz and Klapper, 2015)
   - Incentivized decisions: Inefficient discriminatory choices are costly

Our contribution

We use our lab-in-the-field to answer three main questions:

1. Evidence of (in)direct gender discrimination?
2. Who discriminates? Apply a causal forest algorithm (Wager and Athey, 2018)
3. Nature of discrimination?
    - Accurate statistical discrimination (Phelps, 1972)
    - Discrimination involving bias: taste-based (Becker, 1957), implicit (Bertrand et al., 2005), inaccurate statistical (Bohren et al., 2019)

Our contribution: Focus on guarantors

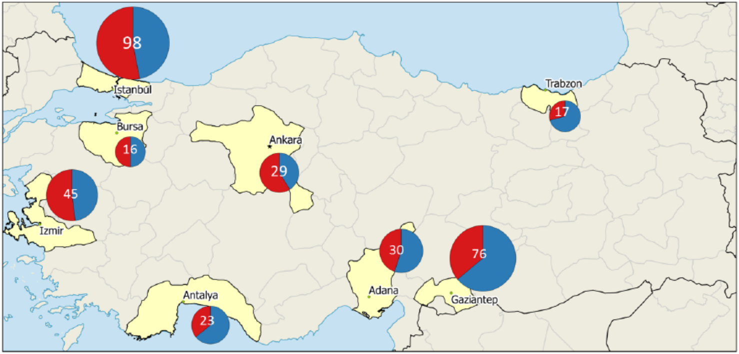
- Widespread in emerging markets, EU, US
- “Active collateral”: guarantors monitor borrowers (Banerjee, Besley, and Guinnane, 1994)
- Based on borrowers’ social capital and the threat of social sanctions
- Turkish context: "second line of defense" to put extra pressure on (some) borrowers

Road map

The experiment

Large Turkish bank: 334 lending staff, 22 sessions, 8 cities

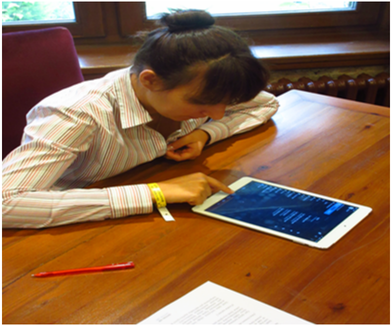
Figure 1: Geographical distribution of participants across the Turkish bank branches



Experimental design

- Two rounds of four loan applications
- We randomized applicant gender:
  - Ali; Emine; Mustafa; Mehmet; Zeynep; Fatma; Ahmet; Ayse
- Loan officers had to take incentivized decisions on approval, amount, guarantor, subjective repayment probability (0-100%)
- Each file reviewed by 13.4 participants: within-file estimate of gender discrimination

Experimental setting



Experimental design

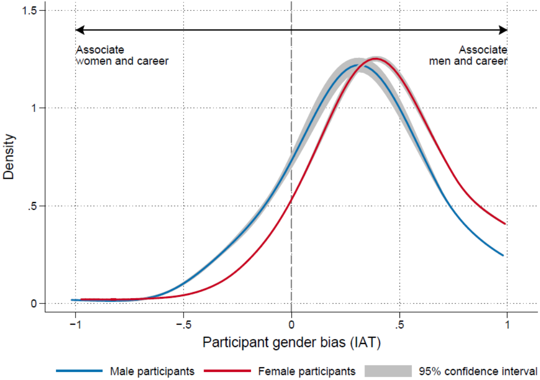
- Use 100 real-life files (loan applications)
  - Each file reviewed by on average 13.4 participants per round
  - Allows for within-file estimate of gender discrimination
- "Gender-neutral" files, stratify by region, gender, firm size
- Performing, NPL, rejected: 2-1-1

Measuring implicit gender bias

- Implicit Association Test
  - Sorting "Female" words with "Family" words and "Male" words with "Career" words (**stereotypical task**)
  - Sorting "Female" words with "Career" words and "Male" words with "Family" words (**non-stereotypical task)**
- Record time in milliseconds
- IAT score: Normalized difference in mean response time between both tasks
- Higher score = higher implicit bias

Implicit gender bias: male vs. female loan officers

Figure 2: Participant gender bias (IAT), by participant sex



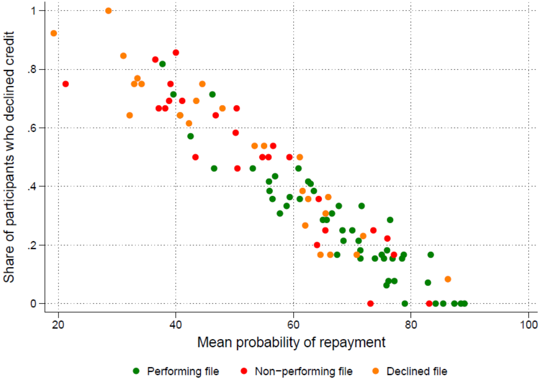
Notes: This figure shows a local polynomial smooth with 95 per cent confidence intervals of the variable *Participant gender bias (IAT)* for male (blue) and female (red) participants, respectively. The combined two-sample Kolmogorov-Smirnov test statistic is 0.181 and has a p-value of 0.01.

Road map

Data and estimation

Expected repayment and loan rejection rates

Figure 3: Expected repayment and loan rejection rates



Notes: The x-axis is the within-file mean, across participants, of the subjective repayment probability. The y-axis is the share of participants who declined the loan application. The figure is based on the first round of the experiment only.

Estimation strategy

$$y_{il} = \alpha + \beta \cdot G_{il} + \varphi_l + \epsilon_{il}$$

- y_{il} Outcome when officer *i* evaluates file *l*
- G_{il} Randomized gender when officer *i* evaluates file *l*
- ϕ_l File FE
- ϵ_{il} Error term clustered at the participant level
- Use LASSO to decide on covariates

Road map

Results

Direct discrimination: Baseline results

Table 2: Applicant gender and loan rejection

Dependent variable: Rejection dummy	[1]	[2]	[3]
Female applicant	-0.008	-0.008	-0.008
	(0.024)	(0.024)	(0.024)
R-squared	0.259	0.264	0.259
N	1,336	1,336	1,336
File FE	✓	✓	✓
City FE		✓	
Double LASSO			✓

Notes: The dependent variable is a *Rejection dummy* that equals '1' if the participant declines the credit application and '0' if the participant approves it. In column (3), a double-LASSO procedure is used to select controls from participant covariates and city FE (set of potential controls). The sample is restricted to the first round of the experiment. Cluster robust standard errors are shown in parentheses and clustered at the participant level. Appendix Table A1 contains all variable definitions.

Indirect discrimination: Baseline results

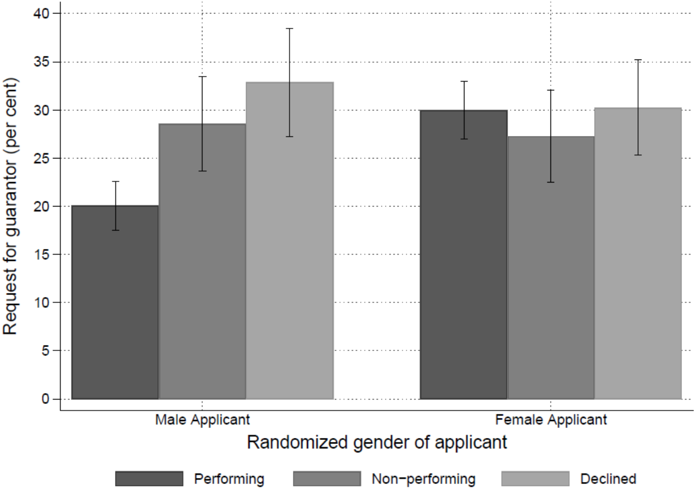
Table 3: Applicant gender and guarantor requirements

Dependent variable: Guarantor dummy			
	[1]	[2]	[3]
Female applicant	0.063	0.058	0.060
	(0.030)	(0.030)	(0.030)
R-squared	0.152	0.188	0.173
N	814	814	814
File FE	✓	✓	✓
City FE		✓	
Double LASSO			✓
Better Lee Bounds		0.057, 0.061	
		[0.000, 0.118]	

Notes: The dependent variable is a *Guarantor dummy* that equals '1' if the participant approves the credit application but requests a guarantor and '0' if the participant approves it without requesting a guarantor. In column (3), a double-LASSO procedure is used to select controls from participant covariates and city FE (set of potential controls). *Better Lee Bounds* refer to Lee (2009) bounds that are tightened through a LASSO selection procedure that considers all participant covariates (Semenova, 2021). Stoye (2009)-adjusted Imbens and Manski (2004) 95% confidence intervals are reported in brackets below these bounds. The sample is restricted to the first round of the experiment. Cluster robust standard errors are shown in parentheses and clustered at the participant level. Appendix Table A1 contains all variable definitions.

Indirect discrimination affects loans that perform well in real life

Figure 4: Guarantor requirements, by loan quality and applicant sex

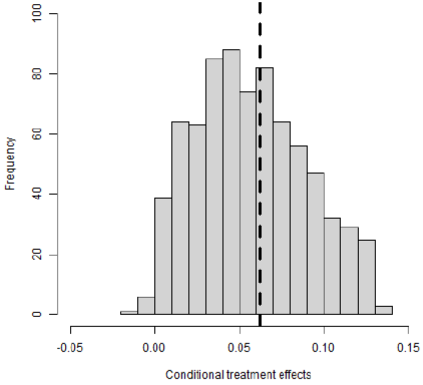


Road map

Who discriminates?

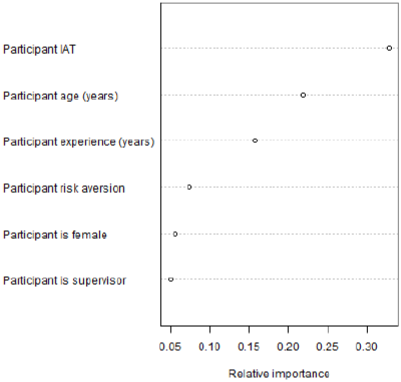
Causal forest: Who discriminates?

Panel A: Distribution of conditional treatment effects

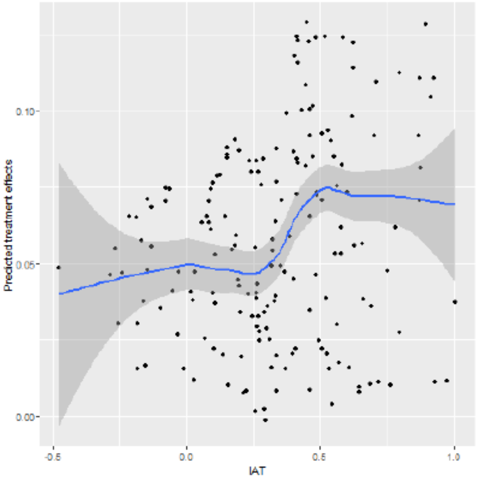


Causal forest: Who discriminates?

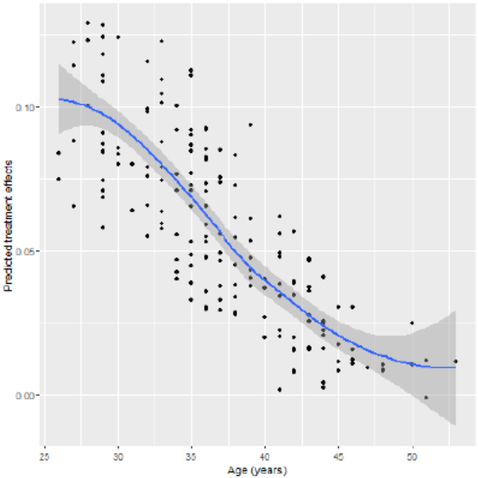
Panel B: Relative importance of covariates



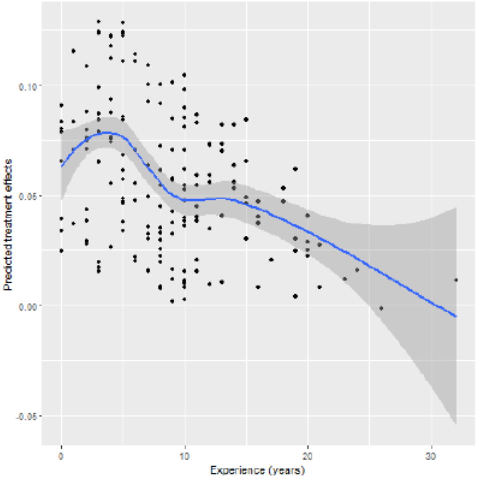
Causal forest: Implicit bias and discrimination intensity



Causal forest: Age and discrimination intensity



Causal forest: Work experience and discrimination intensity

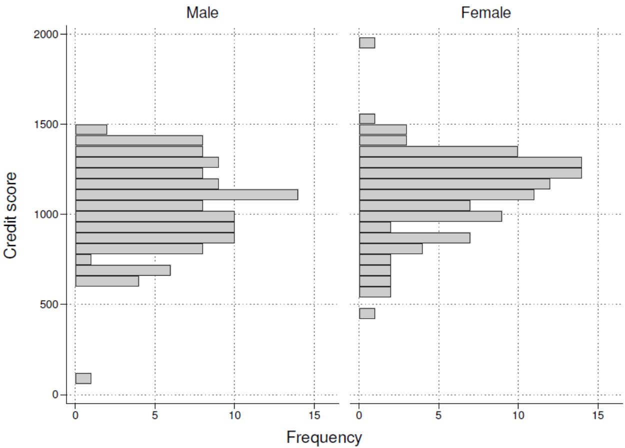


Road map

The nature of discrimination

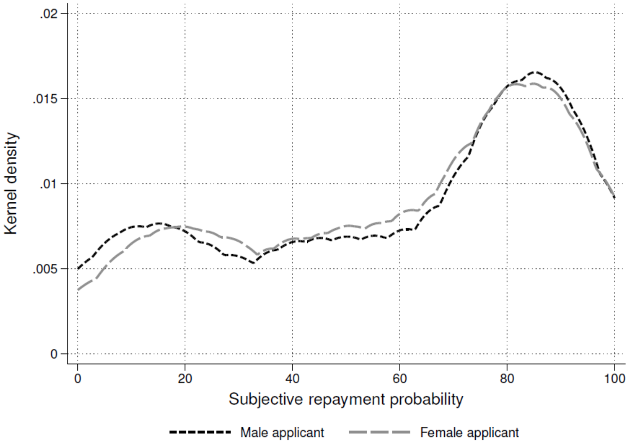
Do loan officers worry about credit risk of female borrowers? (I)

Figure 5: Credit score by original gender of applicant



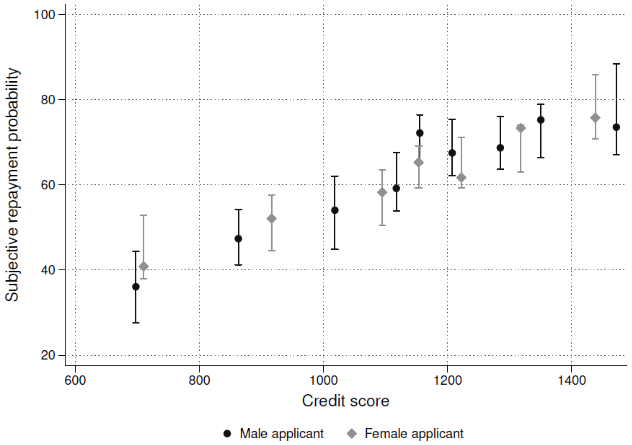
Do loan officers worry about credit risk of female borrowers? (II)

Figure 7: Subjective repayment probability by randomized gender of loan application



Do loan officers worry about credit risk of female borrowers? (III)

Figure 6: Credit score and subjective repayment probability, by randomized applicant gender



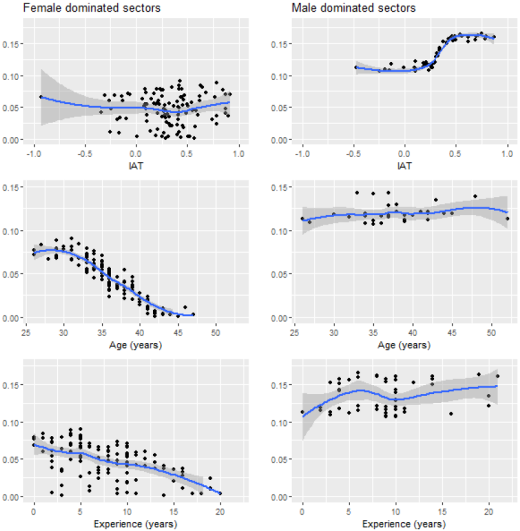
Sectoral gender segregation, implicit bias, and guarantors

Table 6: Applicant gender, sectoral gender composition, and guarantor requirements

Dependent variable: Guarantor dummy						
	Male-dominated sectors	Female-dominated sectors	Male-dominated sectors		Female-dominated sectors	
			Below median IAT	Above median IAT	Below median IAT	Above median IAT
	[1]	[2]	[3]	[4]	[5]	[6]
Female applicant	0.098 (0.055)	0.054 (0.037)	-0.023 (0.091)	0.204 (0.077)	0.014 (0.064)	0.094 (0.053)
t-test p-values	0.255		0.028		0.168	
R-squared	0.114	0.166	0.248	0.352	0.306	0.274
N	219	564	108	106	277	271
File FE	✓	✓	✓	✓	✓	✓
Better Lee Bounds	0.081, 0.094 [-0.030, 0.199]	0.055, 0.057 [-0.023, 0.136]	-0.040, 0.029 [-0.157, 0.121]	0.161, 0.237 [0.013, 0.379]	0.030, 0.082 [-0.062, 0.176]	0.030, 0.082 [-0.029, 0.135]

Notes: The dependent variable is a *Guarantor dummy* that equals '1' if the participant approves the credit application but requests a guarantor and '0' if the participant approves it without requesting a guarantor. Female- and male-dominated sectors are defined by the share of firms with majority female ownership at the 2-digit ISIC industry level using data from the EBRD–World Bank Banking Environment and Performance Survey (BEEPS) V and VI. Female- (male-) dominated firms are those in industries with an above (below) median share of majority female-owned firms. *Better Lee Bounds* refer to Lee (2009) bounds that are tightened through a LASSO selection procedure that considers all participant covariates (Semenova, 2021). Stoye (2009)-adjusted Imbens and Manski (2004) 95% confidence intervals are reported in brackets below these bounds. The sample is restricted to the first round of the experiment. Cluster robust standard errors are shown in parentheses and clustered at the participant level. Appendix Table A1 contains all variable definitions.

CATE in male vs. female sectors



To sum up

- We present evidence of gender-biased guarantor requirements (+26%)
- Concentrated among young, inexperienced, and implicitly biased loan officers...
- ... who <u>do not</u> believe women to be riskier borrowers but who <u>do</u> resort to stereotypes when women apply for loans in male-dominated sectors

Implications

- *"not only the institutional and governance structure of financial institutions matters, but also the gender of the people operating in a given bank structure"* (Beck et al., 2013, p.5)
- Our results: Underlying officer traits—implicit gender bias and experience, which correlate with gender—are more important than gender as such

Implications (II)

- In general: limit ambiguity, time pressure, and distraction so that implicit bias does not become explicit
- Option 1: Bank-wide or branch-wide targets for lending to women without guarantor (comply-or-explain)
- Option 2: Integrate successful female entrepreneurs into training programs to increase visibility for loan officers
- Option 3: Add more senior (i.e. experienced) loan officers to junior teams

Thank you!

Further comments and suggestions: dehaasr@ebrd.com

Latest version of the paper: www.ralphdehaas.com