Bad Taste: Gender Discrimination in Consumer Credit Markets

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NBER Summer Institute
Gender in the Economy Group
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Gender Gaps in Access to Credit

Bank Account Ownership: Men vs Women
(Global Findex Data 2017, World Bank)

- In developing countries, men have more access to credit markets than women.
- Still, the role played by discriminatory actions against women cannot be discarded (Alesina et al. 2013).
- Do banks discriminate against women?

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- Such inequalities are stemming in part from gender gaps originated in the labor market (*Hausman et al. 2009, Goldin 2014, Demirguc-Kunt et al. 2017*).
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**Motivation**

**Experiment**

**Results**

**Conclusion**
In developing countries, men have more access to credit markets than women.


Still, the role played by discriminatory actions against women cannot be discarded (Alesina et al. 2013).

Do banks discriminate against women?
Why study gender discrimination in credit markets?

- Uncovering gender discrimination and its mechanisms is critical for an appropriate welfare analysis of credit markets.
  - Taste-based discrimination on credit lending can lead to welfare loss (Becker 1957).
  - Statistical discrimination is argued to be efficient (Phelps 1972, Arrow 1973).

  However, this only holds under the assumption that loan officers' beliefs about the gender group distribution over the relevant outcomes are "accurate" (Borhen et al. 2019).
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How to identify gender discrimination in credit markets?

- Identifying gender discrimination using observational data is hard

\[ \mathbb{E}(Approval_{ijlk}) = f(Gender_i, \ Applicant_i, \ Officer_j, \ Loan_l, \ Bank_k) \]

- Set of applicant level confounders is short and observable

\[ Applicant_i = f(Demographics_i, \ Income_i, \ Debt_i, \ CreditHistory_i) \]

- Main problem is about officer’s unobservables

\[ Officer_j = f(Demographics_j, \ldots \ (Unobservables: \ Tastes_j, \ Beliefs_j)) \]

- Manipulating applicant’s gender is unfeasible – Experian, TransUnion, or Equifax allows loan officers to easily identify false loan requests.

- Solution?: Randomized correspondence study with real borrowers
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This paper

- **Correspondence Study** in consumer credit market in Chile. We randomly assign *loan requests* (of *random amount and length*) to *male* and *female* prospective borrowers who then submit the assigned requests to randomly assigned *loan officers*.

- What’s novel in this paper?
  - Experimental borrowers and officers interact in a real setting.
  - The experiment fully covers the market of consumer lending.
  - Examine *taste-based discrimination* by eliciting gender preferences of loan officers.
  - Examine "inaccurate statistical discrimination" by implementing an Information experiment aimed at changing the officers' beliefs about repayment capacity of men versus women.
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Approval rate of loan requests submitted by female applicants is **18% lower** compared to male counterparts.

- Estimated **forgone profits** of USD 5.8 M per year ≡ annual cost of hiring 4% of the officer labor force in the banking system.
- Gender discrimination mostly driven by **male officers** who are gender-biased, suggesting **taste-based discrimination**.
- Information treatment did not decrease gender discrimination → we discard “inaccurate” statistical discrimination.

Market competition attenuates gender discrimination, especially among pro-male officers, which meets **Becker 1957**.
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Stage 1 - Borrowers Recruitment

1,600 loan requests:
- random amount ($1,000 - $14,000)
- random length (12 - 60 months)

400 men and women
(statistically balanced)

600 loan officers
(half treatment, half control)
Stage 2 - Randomize Loan Requests

1,600 loan requests:
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- random length (12 - 60 months)

random assignment

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Stage 3 - Randomize Loan Officers

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random assignment

400 men and women
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random assignment

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**Example of a text-standardized Loan Request**

Dear Mr./Mrs. [Loan Officer’s Name],

I am quoting loan conditions, and I got your email. I would like to obtain a personal loan in the amount of 5 million CLP. I want to repay in 24 months. My RUT is [tax identifier number]. My Monthly salary is $750,000 CLP. Please see attached my wage settlement and social security contributions.

Sincerely,

[Tester’s Name]

- Testers were not allowed to negotiate credit conditions when dealing with loan officers inquiries
- We monitor all the tester-officer interactions
<table>
<thead>
<tr>
<th>Chapter</th>
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</tr>
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<tbody>
<tr>
<td>1</td>
<td>Motivation</td>
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</tr>
<tr>
<td>4</td>
<td>Conclusion</td>
</tr>
</tbody>
</table>
Estimating Gender Discrimination

- Effects on the extensive margin
  - Response rate
  - Approval rate

\[ Y_{ijkt} = \alpha + \beta \text{Female}_{li} + \gamma \text{OffGender}_{j} + \mu_k + \delta_l + \theta_t + \rho T_j + \eta X_i + \pi Z_j + \varepsilon_{ijkt} \]
Gender Discrimination

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<table>
<thead>
<tr>
<th></th>
<th>Loan Request was Responded (=1)</th>
<th>Loan Request was Approved (=1)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Unadjusted Mean Diff.</td>
<td>OLS Estimate ((\beta))</td>
</tr>
<tr>
<td>Female (=1)</td>
<td>-0.010</td>
<td>-0.016</td>
</tr>
<tr>
<td></td>
<td>(0.023)</td>
<td>(0.023)</td>
</tr>
<tr>
<td>Obs.</td>
<td>1,313</td>
<td>1,313</td>
</tr>
<tr>
<td>Mean Male</td>
<td>0.861</td>
<td>0.861</td>
</tr>
</tbody>
</table>

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Gender Discrimination

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Loan Officers’ Beliefs about Female/Male Clients

“Which is the **most important problem** you face when dealing with Female/Male clients?”

<table>
<thead>
<tr>
<th>Main Problem with Female Clients</th>
<th>Main Problem with Male Clients</th>
<th>Mean Diff.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low repayment rates</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Uninformed of financial products</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Excessive administrative duties</td>
<td></td>
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<td></td>
<td></td>
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<th>Main Problem with Female Clients</th>
<th>Main Problem with Male Clients</th>
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</tr>
</thead>
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<tr>
<td>Low repayment rates</td>
<td>0.033</td>
<td>0.156</td>
<td>-0.122***</td>
</tr>
<tr>
<td>Uninformed of financial products</td>
<td>0.277</td>
<td>0.302</td>
<td>-0.025</td>
</tr>
<tr>
<td>Excessive administrative duties</td>
<td>0.138</td>
<td>0.119</td>
<td>0.019</td>
</tr>
<tr>
<td>Difficult to communicate</td>
<td>0.105</td>
<td>0.149</td>
<td>-0.045**</td>
</tr>
<tr>
<td>Too tough, require quick responses</td>
<td><strong>0.447</strong></td>
<td>0.273</td>
<td><strong>0.173</strong>*</td>
</tr>
</tbody>
</table>
If you had the chance to choose the optimal distribution of male and female clients in your portfolio: “What would you choose among the following 5 possible choices?”

<table>
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<tr>
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<th>Choice 2</th>
<th>Choice 3</th>
<th>Choice 4</th>
<th>Choice 5</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Prop. Male</strong></td>
<td>20%</td>
<td>40%</td>
<td>50%</td>
<td>60%</td>
</tr>
<tr>
<td><strong>Prop. Female</strong></td>
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<th>Neutral</th>
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<td>50%</td>
</tr>
<tr>
<td>Prop. Female</td>
<td></td>
<td></td>
</tr>
<tr>
<td>80%</td>
<td>60%</td>
<td>50%</td>
</tr>
<tr>
<td>Actual Choice</td>
<td></td>
<td></td>
</tr>
<tr>
<td>9%</td>
<td>63%</td>
<td>28%</td>
</tr>
</tbody>
</table>
Loan Officers’ Preferences about Female/Male Clients

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<td><strong>Choice 1</strong></td>
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<td>50%</td>
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<td>50%</td>
<td>50%</td>
<td>40%</td>
</tr>
<tr>
<td><strong>Choice 4</strong></td>
<td>60%</td>
<td>40%</td>
<td>20%</td>
</tr>
<tr>
<td><strong>Choice 5</strong></td>
<td>80%</td>
<td>20%</td>
<td></td>
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</table>

Actual Choice

- 9%
- 63%
- 28%

Are these preferences guided by taste-based attributes?
→ We answer this through a **Gift Experiment**
### Gift Experiment: Testing construct validity of gender preferences measure

<table>
<thead>
<tr>
<th></th>
<th>Only Female Officers</th>
<th>Only Male Officers</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>If donate (= 1)</td>
<td>If donate (= 1)</td>
</tr>
<tr>
<td>Donee’s Name is Fem. (= 1)</td>
<td>-0.035 (0.053)</td>
<td>-0.028 (0.076)</td>
</tr>
<tr>
<td>Officer is Pro-Male (= 1)</td>
<td>0.065 (0.083)</td>
<td></td>
</tr>
<tr>
<td>Donee’s Name is Fem. × (Officer is Pro-Male)</td>
<td>-0.043 (0.141)</td>
<td></td>
</tr>
<tr>
<td>Obs.</td>
<td>411</td>
<td>411</td>
</tr>
<tr>
<td>Mean if Donee’s Name is Masc.</td>
<td>0.584</td>
<td>0.584</td>
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</table>

**Note:** Significant at the 1% level.
Motivation

Gender Pref. and Discrimination, by Officer’s Gender

Experiment

Results

Conclusion

Female-Male Mean Difference on Loan Approval Rates, by Loan Officer's Gender and Gender Preference

- Female-Male Mean Difference
- Not-Pro-Male
- Pro-Male

Male Officers

Female Officers

Loan Officer's Gender Preference

- Mean Diff.
- 90% CI

Standard errors clustered at the region-bank level

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Male Officers and Gender Discrimination, by Bank

Distribution across Banks

...Scatterplot

Bank-level Female-Male Mean Difference on Loan Approval Rate and Proportion of Male Officers per Bank

-1.269*** (0.119)

0.033 (0.368)

Robust standard errors in parenthesis

***Significant at 1% level.

Point Estimates

Linear Fit

Linear Fit (no outliers)

Proportion of Male Officers per Bank

90% CI  Mean Diff.  90% CI  Prop. Male

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Official statistics from SBIF (2018) show that female clients have lower delinquency rates than males, suggesting that (inaccurate) statistical discrimination might also be at work.

Information Experiment aimed to “correct" biased gender beliefs among loan officers.

“Did you know that female borrowers pay more for consumer credit than males? A recent report released by SBIF (2018) shows that women pay interest rates that are, on average, 15% higher relative to those paid by men. This is even though the same report also shows that female borrowers exhibit repayment rates that are significantly higher compared to male borrowers. Gender discrimination against women may bring negative consequences for women who aim to access the consumer credit market as well as for our economy as it might be inefficient and damaging for productivity."
Official statistics from *SBIF (2018)* show that female clients have **lower delinquency rates** than males, suggesting that (inaccurate) statistical discrimination might also be at work.

Information Experiment aimed to “correct" biased gender beliefs among loan officers.
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### Information Treatment Effects, by Gender Preference

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<tr>
<td></td>
<td>Loan Request was Responded (= 1)</td>
<td>Loan Request was Approved (= 1)</td>
</tr>
<tr>
<td>Female (= 1)</td>
<td>-0.016 (0.026)</td>
<td>-0.033 (0.032)</td>
</tr>
<tr>
<td>Inf. Treat. (= 1)</td>
<td>0.001 (0.030)</td>
<td>-0.005 (0.029)</td>
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<tr>
<td>Female × (Inf. Treat.)</td>
<td>-0.007 (0.037)</td>
<td>0.004 (0.057)</td>
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<td>Obs.</td>
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- **Overconfidence bias** (*Heidhues, Köszegi, and Strack 2019*)
  - Pro-male loan officers have self-serving views about discrimination, that is, they **overestimate** the degree of discrimination against any group whose preferences they are personally aligned with (e.g. male applicants) and **underestimate** discrimination against any group they compete with or are not aligned with (e.g. female applicants).
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Market Concentration and Gender Discrimination

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\[ \text{HH Index} = \left(\frac{1}{100}\right) \times \sum_{k=1}^{K} s_k^2 \]

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Raimundo Undurraga, U. of Chile

July 25th, 2020, NBER Summer Institute - Gender in the Economy Group
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Bad Taste: Gender Discrimination in Consumer Credit Markets

Thanks for watching!

(We appreciate comments)

raimundo.undurraga@dii.uchile.cl