Bad Taste: Gender Discrimination in Consumer Credit Markets

Ana María Montoya
U. of Chile

Eric Parrado
Inter-American Development Bank

Alex Solís
Uppsala

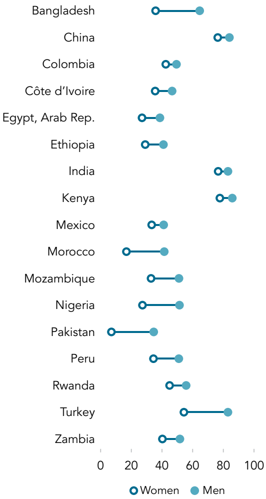
Raimundo Undurraga
U. of Chile

NBER Summer Institute
Gender in the Economy Group
July 25th, 2020

Table of Contents

Gender Gaps in Access to Credit

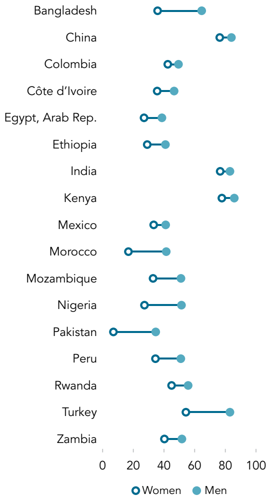
Bank Account Ownership: Men vs Women
(*Global Findex Data 2017, World Bank*)



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

Gender Gaps in Access to Credit

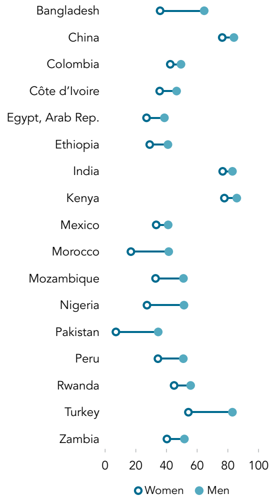
Bank Account Ownership: Men vs Women
(*Global Findex Data 2017, World Bank*)



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

Gender Gaps in Access to Credit

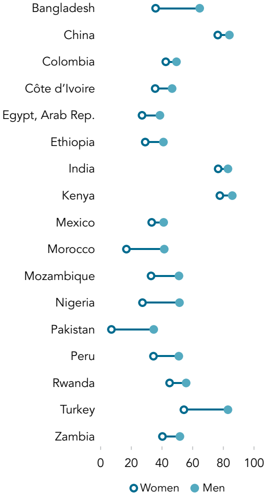
Bank Account Ownership: Men vs Women
(*Global Findex Data 2017, World Bank*)



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

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
- 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*).
- 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 outcome are "accurate" (*Bohren et al. 2019*).

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 outcome are **"accurate"** (*Borhen et al. 2019*).

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 outcome are **"accurate"** (*Borhen et al. 2019*).

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 outcome are **"accurate"** (*Borhen et al. 2019*).

How to identify gender discrimination in credit markets?

- Identifying gender discrimination using observational data is hard

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

- Set of applicant level confounders is short and observable

$$Applicant_i = f(Demographics_i, \quad Income_i, \quad Debt_i, \quad CreditHistory_i)$$

- Main problem is about officer's unobservables

$$Officer_j = f(Demographics_j, \ldots \quad (\underline{Unobservables} : Tastes_j, \quad Beliefs_j))$$

- 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

How to identify gender discrimination in credit markets?

- Identifying gender discrimination using observational data is hard

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

- Set of applicant level confounders is short and observable

$$Applicant_i = f(Demographics_i, \quad Income_i, \quad Debt_i, \quad CreditHistory_i)$$

- Main problem is about officer's unobservables

$$Officer_j = f(Demographics_j, \ldots \quad (\underline{Unobservables} : Tastes_j, \quad Beliefs_j))$$

- 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

How to identify gender discrimination in credit markets?

- Identifying gender discrimination using observational data is hard

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

- Set of applicant level confounders is short and observable

$$Applicant_i = f(Demographics_i, \quad Income_i, \quad Debt_i, \quad CreditHistory_i)$$

- Main problem is about officer's unobservables

$$Officer_j = f(Demographics_j, \dots \quad (\underline{Unobservables} : Tastes_j, \quad Beliefs_j))$$

- 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

How to identify gender discrimination in credit markets?

- Identifying gender discrimination using observational data is hard

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

- Set of applicant level confounders is short and observable

$$Applicant_i = f(Demographics_i, \quad Income_i, \quad Debt_i, \quad CreditHistory_i)$$

- Main problem is about officer's unobservables

$$Officer_j = f(Demographics_j, \ldots \quad (\underline{Unobservables} : Tastes_j, \quad Beliefs_j))$$

- 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

How to identify gender discrimination in credit markets?

- Identifying gender discrimination using observational data is hard

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

- Set of applicant level confounders is short and observable

$$Applicant_i = f(Demographics_i, \quad Income_i, \quad Debt_i, \quad CreditHistory_i)$$

- Main problem is about officer's unobservables

$$Officer_j = f(Demographics_j, \ldots \quad (\underline{Unobservables} : Tastes_j, \quad Beliefs_j))$$

- 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

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.

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.

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.

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.

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.

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.

Preview of Results

- 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 $\equiv$ 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 $\rightarrow$ we discard *"inaccurate" statistical discrimination*
- **Market competition** attenuates gender discrimination, especially among pro-male officers, which meets *Becker 1957*.

Preview of Results

- 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 $\equiv$ 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 $\rightarrow$ we discard *“inaccurate" statistical discrimination*
- **Market competition** attenuates gender discrimination, especially among pro-male officers, which meets *Becker 1957*.

Preview of Results

- 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 $\equiv$ 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 $\rightarrow$ we discard *“inaccurate" statistical discrimination*
  - However, information treatment increased gender discrimination among pro-male officers, a counterreaction that reinforces the taste-based mechanism $\rightarrow$ a potential explanation is **overconfidence bias** (*Heidhues, Kőszegi, and Strack 2019*).
- **Market competition** attenuates gender discrimination, especially among pro-male officers, which meets *Becker 1957*.

Preview of Results

- 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 $\equiv$ 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 $\rightarrow$ we discard *"inaccurate" statistical discrimination*
  - However, information treatment increased gender discrimination among pro-male officers, a counterreaction that reinforces the taste-based mechanism $\rightarrow$ a potential explanation is **overconfidence bias** (*Heidhues, Köszegi, and Strack 2019*).
- **Market competition** attenuates gender discrimination, especially among pro-male officers, which meets *Becker 1957*.

Preview of Results

- 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 $\equiv$ 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 $\rightarrow$ we discard *"inaccurate" statistical discrimination*
  - However, information treatment increased gender discrimination among pro-male officers, a counterreaction that reinforces the taste-based mechanism $\rightarrow$ a potential explanation is **overconfidence bias** (*Heidhues, Köszegi, and Strack 2019*).
- **Market competition** attenuates gender discrimination, especially among pro-male officers, which meets *Becker 1957*.

Preview of Results

- 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 $\equiv$ 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 $\rightarrow$ we discard *"inaccurate" statistical discrimination*
  - However, information treatment increased gender discrimination among pro-male officers, a counterreaction that reinforces the taste-based mechanism $\rightarrow$ a potential explanation is **overconfidence bias** (*Heidhues, Kőszegi, and Strack 2019*).
- **Market competition** attenuates gender discrimination, especially among pro-male officers, which meets *Becker 1957*.

Table of Contents

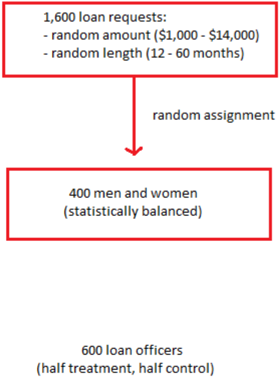
Stage 1 - Borrowers Recruitment

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

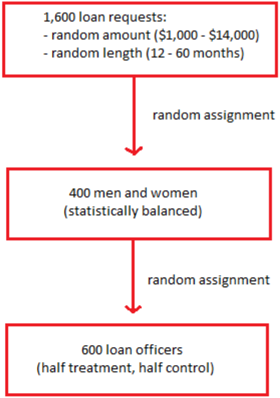
400 men and women
(statistically balanced)

600 loan officers
(half treatment, half control)

Stage 2 - Randomize Loan Requests



Stage 3 - Randomize Loan Officers



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 of Contents

Estimating Gender Discrimination

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

$$Y_{lijkt} = \alpha + \beta Female_{li} + \gamma OffGender_j + \mu_k + \delta_l + \theta_t + \rho T_j + \eta X_i + \pi Z_j + \varepsilon_{lijkt}$$

Gender Discrimination

$$Y_{lijkt} = \alpha + \beta Female_{li} + \gamma OffGender_j + \mu_k + \delta_l + \theta_t + \rho T_j + \eta X_i + \pi Z_j + \varepsilon_{lijkt}$$

	Loan Request was Responded (=1)		Loan Request was Approved (=1)	
	Unadjusted Mean Diff.	OLS Estimate (β)	Unadjusted Mean Diff.	OLS Estimate (β)
Female (=1)	-0.010 (0.023)	-0.016 (0.023)		
Obs.	1,313	1,313		
Mean Male	0.861	0.861		

Gender Discrimination

$$Y_{lijkt} = \alpha + \beta Female_{li} + \gamma OffGender_j + \mu_k + \delta_l + \theta_t + \rho T_j + \eta X_i + \pi Z_j + \varepsilon_{lijkt}$$

	Loan Request was Responded (=1)		Loan Request was Approved (=1)	
	Unadjusted Mean Diff.	OLS Estimate (β)	Unadjusted Mean Diff.	OLS Estimate (β)
Female (=1)	-0.010 (0.023)	-0.016 (0.023)	-0.066*** (0.023)	-0.064*** (0.017)
Obs.	1,313	1,313	1,313	1,313
Mean Male	0.861	0.861	0.349	0.349

Loan Officers' Beliefs about Female/Male Clients

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

	Main Problem with **Female** Clients	Main Problem with **Male** Clients	Mean Diff.
Low repayment rates			
Uninformed of financial products			
Excessive administrative duties			
Difficult to communicate			
Too tough, require quick responses			

Loan Officers' Beliefs about Female/Male Clients

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

	Main Problem with **Female** Clients	Main Problem with **Male** Clients	Mean Diff.
Low repayment rates	0.033	0.156	-0.122***
Uninformed of financial products	0.277	0.302	-0.025
Excessive administrative duties	0.138	0.119	0.019
Difficult to communicate	0.105	0.149	-0.045**
Too tough, require quick responses	**0.447**	0.273	0.173***

Loan Officers' Preferences about Female/Male Clients

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?"***

	Choice 1	Choice 2	Choice 3	Choice 4	Choice 5
Prop. Male	20%	40%	50%	60%	80%
Prop. Female	80%	60%	50%	40%	20%

Loan Officers' Preferences about Female/Male Clients

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?"***

	Pro-Female		Neutral	Pro-Male	
	Choice 1	Choice 2	Choice 3	Choice 4	Choice 5
Prop. Male	20%	40%	50%	60%	80%
Prop. Female	80%	60%	50%	40%	20%
Actual Choice	9%		63%	28%	

Loan Officers' Preferences about Female/Male Clients

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?"***

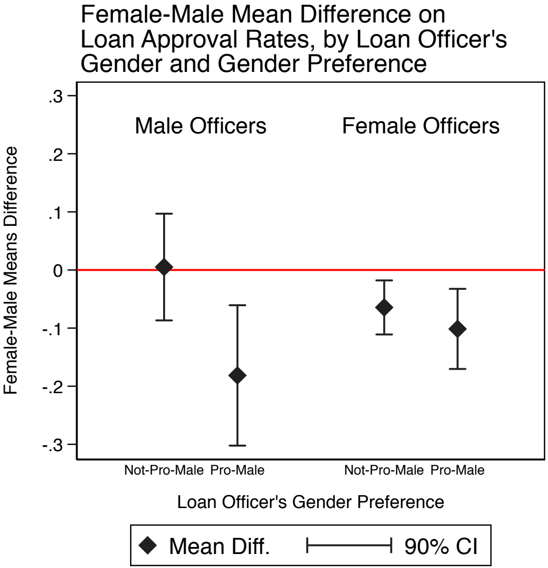
	Pro-Female		Neutral	Pro-Male	
	Choice 1	Choice 2	Choice 3	Choice 4	Choice 5
Prop. Male	20%	40%	50%	60%	80%
Prop. Female	80%	60%	50%	40%	20%
Actual Choice	9%		63%	28%	

- Are these preferences guided by taste-based attributes?
  $\rightarrow$ We answer this through a **Gift Experiment**

Gift Experiment: Testing construct validity of gender preferences measure

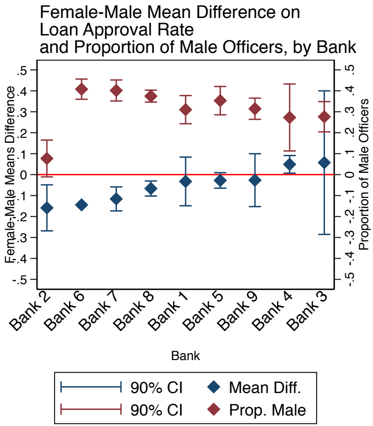
	Only Female Officers		Only Male Officers	
	If donate (= 1)		If donate (= 1)	
Donee's Name is Fem. (= 1)	-0.035	-0.028	-0.094*	-0.018
	(0.053)	(0.076)	(0.057)	(0.057)
Officer is Pro-Male (= 1)		0.065		0.224*
		(0.083)		(0.117)
Donee's Name is Fem. × (Officer is Pro-Male)		-0.043		**-0.402***
		(0.141)		**(0.233)**
Obs.	411	411	218	218
Mean if Donee's Name is Masc.	0.584	0.584	0.717	0.717

Gender Pref. and Discrimination, by Officer's Gender

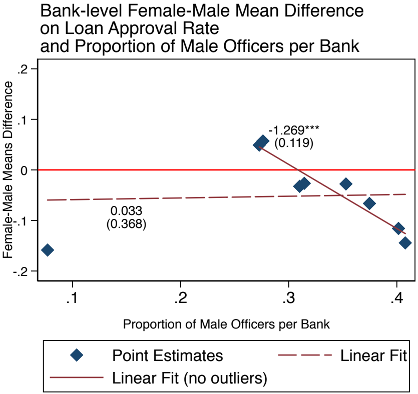


Male Officers and Gender Discrimination, by Bank

.......Distribution across Banks



...Scatterplot



Robust standard errors in parenthesis
***Significant at 1% level.

(Inaccurate) Statistical Discrimination

- 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.”*

(Inaccurate) Statistical Discrimination

- 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."*

(Inaccurate) Statistical Discrimination

- 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."*

Information Treatment Effects, by Gender Preference

	Only Not-Pro-Male Off.		Only Pro-Male Off.	
	Loan Request was Responded (= 1)	Loan Request was Approved (= 1)	Loan Request was Responded (= 1)	Loan Request was Approved (= 1)
Female (= 1)	-0.016 (0.026)	-0.033 (0.032)	0.063 (0.085)	-0.125* (0.076)
Inf. Treat.(= 1)	0.001 (0.030)	-0.005 (0.029)	0.040 (0.080)	0.075 (0.117)
Female $\times$ (Inf. Treat.)	-0.007 (0.037)	0.004 (0.057)	**-0.130*** (0.077)	**-0.089** (0.084)
Obs.	957	957	356	356

Why Pro-male counter-reacted to treatment message?

- **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).
  - *Bohnet 2016* shows that explicit diversity training programs in US corporations have made between-group differences more salient, which in turn have generated more discrimination against minority groups, not less.

Why Pro-male counter-reacted to treatment message?

- **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).
  - *Bohnet 2016* shows that explicit diversity training programs in US corporations have made between-group differences more salient, which in turn have generated more discrimination against minority groups, not less.

Why Pro-male counter-reacted to treatment message?

- **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).
  - *Bohnet 2016* shows that explicit diversity training programs in US corporations have made between-group differences more salient, which in turn have generated more discrimination against minority groups, not less.

Market Concentration and Gender Discrimination

- *Becker 1957*: Provided that banks have constant returns to scale and that men and women are equally skilled, increasing competition should reduce gender discrimination.
- HH Index = $(1/100) \times \sum_{k=1}^{K} s_k^2$

	Only Not-Pro-Male Off.		Only Pro-Male Off.	
	Responded (= 1)	Approved (= 1)	Responded (= 1)	Approved (= 1)
Female (= 1)	0.068 (0.065)	0.085 (0.092)	0.071 (0.115)	0.201 (0.190)
HH Index	0.004*** (0.001)	-0.007** (0.003)	0.007 (0.008)	0.020* (0.011)
Female × HH Index	-0.006** (0.003)	-0.008* (0.005)	-0.005 (0.008)	**-0.025**** **(0.012)**
Obs.	957	957	356	356

Market Concentration and Gender Discrimination

- *Becker 1957*: Provided that banks have constant returns to scale and that men and women are equally skilled, increasing competition should reduce gender discrimination.
- HH Index = $(1/100) \times \sum_{k=1}^{K} s_k^2$

	Only Not-Pro-Male Off.		**Only Pro-Male Off.**	
	Responded (= 1)	Approved (= 1)	Responded (= 1)	Approved (= 1)
Female (= 1)	0.068 (0.065)	0.085 (0.092)	0.071 (0.115)	0.201 (0.190)
HH Index	0.004*** (0.001)	-0.007** (0.003)	0.007 (0.008)	0.020* (0.011)
Female × HH Index	-0.006** (0.003)	-0.008* (0.005)	-0.005 (0.008)	**-0.025**** **(0.012)**
Obs.	957	957	356	356

Table of Contents

Bottom Line

- Gender discrimination in the consumer credit market exists and it's large ($\approx$18%), at least for the case of Chile.
  - Non-negligible **Efficiency Costs** $\rightarrow$ 5.8 million dollars per year $\equiv$ annual cost of hiring 4% of the officer labor force in the banking system.
- Effects driven by **taste-based** sources on the part of **male officers**.
- Explicit Information treatments unlikely to be successful
- Increasing competition appears to be an effective way to reduce gender discrimination.
- Future research: Role of Fintech technologies and automation? (*Bartlett et al. 2019, Gillis and Spiess 2020, Fuster et al. 2020*)

Bottom Line

- Gender discrimination in the consumer credit market exists and it's large ($\approx$18%), at least for the case of Chile.
    - Non-negligible **Efficiency Costs** $\rightarrow$ 5.8 million dollars per year $\equiv$ annual cost of hiring 4% of the officer labor force in the banking system.
- Effects driven by **taste-based** sources on the part of **male officers**.
- Explicit Information treatments unlikely to be successful
    - Interventions oriented to directly reduce overconfidence bias? Role of culture?
- Increasing competition appears to be an effective way to reduce gender discrimination.
- Future research: Role of Fintech technologies and automation? (*Bartlett et al. 2019, Gillis and Spiess 2020, Fuster et al. 2020*)

Bottom Line

- Gender discrimination in the consumer credit market exists and it's large ($\approx$18%), at least for the case of Chile.
    - Non-negligible **Efficiency Costs** $\rightarrow$ 5.8 million dollars per year $\equiv$ annual cost of hiring 4% of the officer labor force in the banking system.
- Effects driven by **taste-based** sources on the part of **male officers**.
- Explicit Information treatments unlikely to be successful
    - Interventions oriented to directly reduce **overconfidence bias**?
    - Role of **culture**?
- Increasing competition appears to be an effective way to reduce gender discrimination.
- Future research: Role of Fintech technologies and automation? (*Bartlett et al. 2019, Gillis and Spiess 2020, Fuster et al. 2020*)

Bottom Line

- Gender discrimination in the consumer credit market exists and it's large ($\approx$18%), at least for the case of Chile.
  - Non-negligible **Efficiency Costs** $\rightarrow$ 5.8 million dollars per year $\equiv$ annual cost of hiring 4% of the officer labor force in the banking system.
- Effects driven by **taste-based** sources on the part of **male officers**.
- Explicit Information treatments unlikely to be successful
  - Interventions oriented to directly reduce **overconfidence bias**?
  - Role of **culture**?
- Increasing competition appears to be an effective way to reduce gender discrimination.
- Future research: Role of Fintech technologies and automation? (*Bartlett et al. 2019, Gillis and Spiess 2020, Fuster et al. 2020*)

Bottom Line

- Gender discrimination in the consumer credit market exists and it's large ($\approx$18%), at least for the case of Chile.
  - Non-negligible **Efficiency Costs** $\rightarrow$ 5.8 million dollars per year $\equiv$ annual cost of hiring 4% of the officer labor force in the banking system.
- Effects driven by **taste-based** sources on the part of **male officers**.
- Explicit Information treatments unlikely to be successful
  - Interventions oriented to directly reduce **overconfidence bias**?
  - Role of **culture**?
- Increasing competition appears to be an effective way to reduce gender discrimination.
- Future research: Role of Fintech technologies and automation? (*Bartlett et al. 2019, Gillis and Spiess 2020, Fuster et al. 2020*)

Bottom Line

- Gender discrimination in the consumer credit market exists and it's large ($\approx$18%), at least for the case of Chile.
  - Non-negligible **Efficiency Costs** $\rightarrow$ 5.8 million dollars per year $\equiv$ annual cost of hiring 4% of the officer labor force in the banking system.
- Effects driven by **taste-based** sources on the part of **male officers**.
- Explicit Information treatments unlikely to be successful
  - Interventions oriented to directly reduce **overconfidence bias**?
  - Role of **culture**?
- Increasing competition appears to be an effective way to reduce gender discrimination.
- Future research: Role of Fintech technologies and automation? (*Bartlett et al. 2019, Gillis and Spiess 2020, Fuster et al. 2020*)

Bottom Line

- Gender discrimination in the consumer credit market exists and it's large ($\approx$18%), at least for the case of Chile.
  - Non-negligible **Efficiency Costs** $\rightarrow$ 5.8 million dollars per year $\equiv$ annual cost of hiring 4% of the officer labor force in the banking system.
- Effects driven by **taste-based** sources on the part of **male officers**.
- Explicit Information treatments unlikely to be successful
  - Interventions oriented to directly reduce **overconfidence bias**?
  - Role of **culture**?
- Increasing competition appears to be an effective way to reduce gender discrimination.
- Future research: Role of Fintech technologies and automation? (*Bartlett et al. 2019, Gillis and Spiess 2020, Fuster et al. 2020*)

Bottom Line

- Gender discrimination in the consumer credit market exists and it's large ($\approx$18%), at least for the case of Chile.
  - Non-negligible **Efficiency Costs** $\rightarrow$ 5.8 million dollars per year $\equiv$ annual cost of hiring 4% of the officer labor force in the banking system.
- Effects driven by **taste-based** sources on the part of **male officers**.
- Explicit Information treatments unlikely to be successful
  - Interventions oriented to directly reduce **overconfidence bias**?
  - Role of **culture**?
- Increasing competition appears to be an effective way to reduce gender discrimination.
- Future research: Role of Fintech technologies and automation? (*Bartlett et al. 2019*, *Gillis and Spiess 2020*, *Fuster et al. 2020*)

Bad Taste: Gender Discrimination in Consumer Credit Markets

Thanks for watching!

(We appreciate comments)

raimundo.undurraga@dii.uchile.cl