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Preference for women but less preference for indigenous women: A lab-field experiment of loan discrimination in Bolivia

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Abstract A field experiment was performed in a controlled laboratory setting to evaluate if credit officers reject a micro-loan application based on the ethnicity/gender of a potential borrower. Point estimates of a mixed-effects logistic regression suggest that, compared to non-indigenous men, non-indigenous women have twice more chances of loan approval and indigenous women have 1.5 more chances of loan approval. The intervallic results about ethnic discrimination are inconclusive, but some evidence of taste-based discrimination in credit lending favorable for non-indigenous women was found.

Keywords Credit access · gender gaps · indigenous peoples · discrete choice · Bayesian analysis
JEL codes G21 · J15 · C25 · C11

1 Introduction

Altonji and Blank (1999) define discrimination in credit lending as a situation in which potential borrowers who can meet their debt obligations in the same way are treated unequally in a way that is related to an observable characteristic such as ethnicity or gender. 'Unequally' implies that potential borrowers face different credit-rejection rates or receive different credit amounts, conditional on the same characteristics. This study

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presents the results of a laboratory-field experiment performed to test the existence of loan discrimination in the Bolivian credit market.

Recently, the Bolivian government issued regulations to reduce historical discriminatory practices and decrease institutional and market barriers to credit access for micro and small enterprises[1]. Despite these efforts, there still may be discriminatory practices limiting the access of financial services for women and ethnic groups, since Bolivia is a country with several indigenous nations who can be victims of discrimination from credit officers when asking for a loan in a financial institution[2]. As there are no records of ethnicity in credit scoring (since this will be a discriminatory practice itself) it is not possible to use administrative information from financial institutions to assess the extent of discriminatory practices during loan provision. Nevertheless, a lab-field experiment can be performed to evaluate if ethnic/gender discrimination is a barrier limiting access to financial services for micro and small entrepreneurs of Bolivia. To our knowledge, discrimination in credit markets of developing countries was never analyzed by means of an economic lab-field experiment before[3].

[1] See the *Law against racism and all forms of discrimination*, promulgated by President Evo Morales as Law 737 on 10 October 2010, and the *Financial Services Law* of Bolivia from August 2013. In terms of credit access, the new law of financial services sets limits to interest rates and criteria of portfolio allocation for productive activities, and highlights in its article 74 that the access of financial services must be on a basis of equal treatment, without discrimination because of gender, race or cultural identity. Heng (2015) made an evaluation of the impact of the New Financial Services Law in Bolivia and he found that the interest rate caps had an effect on financial inclusion, especially for small borrowers, as microfinance institutions have increased loan sizes and reduced the number of borrowers.

[2] According to World Bank (2015), in Bolivia, extreme poverty for people belonging to indigenous groups in rural areas is still twice that of the non-indigenous—51.6 compared to 22.5 percent—and 64 percent of the household heads in extreme poor households were indigenous, compared to 22 percent of the non-poor household heads. Lundvall et al. (2015) adds that women who belong to indigenous groups in Bolivia have lower education outcomes than any other group, e.g. compared to non-indigenous men, the literacy rate for indigenous women is 15 percentage points lower. This gap in education can create a structural barrier for financial access.

[3] Field experiments on discrimination tend to be focused on correspondence studies for labour markets in developed economies—see Rich (2014) or Bertrand and Duflo (2016) for a survey. Dymski (2006) provides an overview of previous empirical studies of discrimination in the credit market, based on racial redlining, mortgage loan data and audit (in-person) studies. Studies based on observational data as e.g. Deku and Kara (2013) found evidence that households of a racial origin other than white are more likely to be excluded from consumer credit in the UK, while Blanchflower et al. (2003) found that black-owned small businesses are almost three times more likely to have a loan application denied in the U.S. small business credit market. Using also observational data, but this time from a developing country, Nwosu et al. (2015) did not found significant discrimination against women entrepreneurs in formal credit markets of Nigeria, after analyzing the enterprise survey data of this country from 2010. Other studies as Pope and Sydnor (2011) found that in peer-to-peer credit markets (prosper.com) loan listings with blacks in the attached picture are 25 to 35 percent less likely to receive funding than those of whites with similar credit profiles; using also photographs of potential borrowers from prosper.com, Duarte et al. (2012) further showed that borrowers who appear more trustworthy have higher probabilities of having their loans funded, a finding consistent with the trust-intensive nature of lending. In terms of audit studies, Turner et al. (2002) matched Hispanic and African-American testers with

Section 2 explains the experimental design and section 3 the methods of data analysis. Section 4 contains the results and section 5 discusses the results. Complementary analysis can be found in the appendices at the end of the study. The data of the experiment and the codes to replicate the results are available upon request.

2 Experimental Design

The experiment was designed to evaluate whether real credit officers reject a micro-loan application based on the ethnicity/gender of a potential borrower. The experiment can be seen as a laboratory experiment because the treatment was controlled by the researchers, but can also be classified as a field experiment since the outcomes –rejection or approval of the loan application– were generated by real credit officers. See Levitt and List (2009).

Recruitment of participants. Meetings with the executive directors of 8 micro-finance institutions (MFIs) of Bolivia were held to recruit credit officers for the experiment. Following the instructions of the research team, each MFI sorted in alphabetical order its list of credit officers working in the cities of La Paz and El Alto and then provided the names and contact information of the first 10 and the last 10 credit analysts from the list. The contact with every credit officer was performed by phone calls and through e-mails attached with an invitation letter. Eighty six (86) credit officers accepted the invitation to participate in the experiment.

Pilot study. A pilot study was conducted in November 2015, before the official experiment, to identify flaws in the experimental design. The main result of the pilot was that credit officers translate the information of a potential borrower into a final discrete choice (rejection or approval of a loan application) rather than in a continuous probability of loan default. Thus, a dichotomic variable was chosen as the outcome of the experiment.

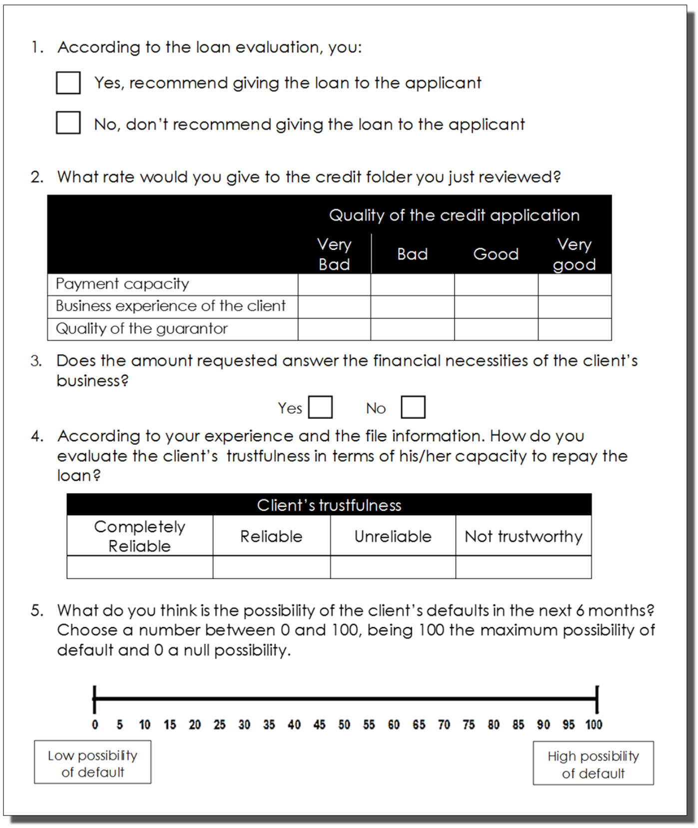
white testers who had roughly equivalent financial backgrounds to evaluate discriminatory treatment when they inquire about loan products. Their results shows that most people of color do not face discriminatory treatment when they inquire about loan products, but in contrast African-American and Hispanic homebuyers face a statistically significant risk of receiving less favorable treatment than comparable whites when they ask mortgage-lending institutions about financing options. Fay and Williams (1993) used an experimental design based on sending a loan application (with a photo of a male or female applicant) to a random sample of loan officers in 200 bank branches of four major trading banks in towns and cities in New Zealand. Fay and Williams found that there was a significant difference in the probability of being granted a loan in favour of the male applicant if the university qualification was absent. In a recent study, Harkness (2016) used Amazon.com's Mechanical Turk workers to evaluate a series of loan applicants whose gender (female or male) and race (black or white) were manipulated. Harkness (2016) found that black men and white women are more disadvantaged relative to black women and white men in their experimental credit market.

Fig. 1 Lab-field experiment

Lab-field experiment. The lab-field experiment was conducted from March 5th to March 12th of 2016 at the Catholic University of San Pablo, in the city of La Paz. A show-up rate of 81% was observed: 70 credit officers of the 86 that accepted the invitation effectively assisted and participated in the experiment. Even if participants were allowed to abandon the activity at any time, everyone stayed until the end of the experiment (Figure 1). At the end of the evaluation, each participant received approximately USD 36 as a payment for their participation.

Experimental procedures. In the first step of the experiment credit officers filled a registration form prepared to obtain demographic information of the participants. Afterwards, a team researcher explained to the participants the purpose of the activity, the payment they will receive and the procedures. Four application files were then delivered to each of the participants. Once everyone had their files, participants were required to state the order in which they wanted to evaluate the four applications. They had 2 minutes to decide this order, until a stopwatch rang. Then, participants were asked to evaluate each application and write answers to the questions of a loan evaluation sheet (Figure 2). After one hour of work, participants were interrupted and they were required to order the files again, but this time in relation to the loan release order they prefer, if any. In the last step of the experiment the research team validated the evaluation of the participants to avoid missing values. The ordering-activities of the experiment were aimed to disentangle taste-based discrimination from statistical discrimination. See Appendix A for details.

Experimental instructions. The explanation highlighted that all of the information in the loan application files was real and corroborated and verified by the research team. Participants that evaluated loan applications



1. According to the loan evaluation, you:

☐ Yes, recommend giving the loan to the applicant

☐ No, don't recommend giving the loan to the applicant

2. What rate would you give to the credit folder you just reviewed?

	Quality of the credit application			
	Very Bad	Bad	Good	Very good
Payment capacity				
Business experience of the client				
Quality of the guarantor				

3. Does the amount requested answer the financial necessities of the client's business?

Yes ☐ No ☐

4. According to your experience and the file information. How do you evaluate the client's trustfulness in terms of his/her capacity to repay the loan?

Client's trustfulness			
Completely Reliable	Reliable	Unreliable	Not trustworthy

5. What do you think is the possibility of the client's defaults in the next 6 months? Choose a number between 0 and 100, being 100 the maximum possibility of default and 0 a null possibility.

0 5 10 15 20 25 30 35 40 45 50 55 60 65 70 75 80 85 90 95 100

Low possibility of default

High possibility of default

Fig. 2 Evaluation sheet provided to the experiment participants

were informed that the experiment was focused on improve the understanding about the process of credit evaluation in micro finance institutions. The participants did not know about the core research question of the experiment (discriminatory behavior) in order to avoid biased attitudes caused by a Hawthorne effect.

Credit application files. Credit applications of four potential borrowers were delivered to the credit officers for evaluation: a loan application from an indigenous-male, a loan application from a non-indigenous-male, a loan application from an indigenous-female and a loan application from a non-indigenous-female. The information of the folders was fictitious but it was based on real and representative credit profiles. Eight categories of information were introduced in the loan folders to support the payment capacity of the potential borrower: (i) personal data of the applicant, (ii) household information, (iii) general information of the economic activity, (iv) information about the credit requested, (v) information about the guarantor and the couple of the applicant, (vi) historical credit reports and assets of the applicant, (vii) detailed economic information of the activity and (viii) proposed payment plan of the loan (Table 1). To further ensure that the information is balanced between application files and isolate its effect on the experiment, the indigenous and non-indigenous names-surnames were exchanged between files for each category of information I, II, III, IV, both for men (I, II) and women (III, IV).

Table 1 Loan application information (in USD)

	Credit file			
	I	II	III	IV
Assets	3947	4085	8248	8237
Amount requested	1020	1050	1312	1341
Sales income	1254	1254	1749	1778
Household spending	207	204	239	249
Final cash balance	67	65	79	83
Monthly payment	60	62	78	78
Collateral's final cash balance	160	176	736	743
Collateral's financial wealth	58855	58841	53724	53659

Treatment design. Pictures and indigenous-sounding names of the potential borrower were used as the 'treatment' of the experiment. The pictures were chosen considering the skin color, face shape (slanted eyes and prominent cheekbones) and age ranges (30 to 45 years old) typical of potential borrowers from the indigenous Aymara nation, an ethnic group of the Andes and Altiplano regions of South America (Buechler and Buechler, 1971). The pictures used in the experiment are available upon request.

Candidate names were selected based on the most frequent names from the official list of voters elaborated by the Electoral Organism of Bolivia *(Organismo Electoral Plurinacional)*. To decide which names are indigenous and which are not, an online survey applied to a non-probabilistic sample of 29 credit officers in the city of La Paz was conducted in October 2015. Each person was asked to connect some features of a person with a particular picture (with and without indigenous appearance) and then they were requested to match the picture with possible names. The results of the survey allowed to clearly identify some names as indigenous and non-indigenous and four of these names/surnames were used in the experiment (Table 2). A similar approach was used by Bertrand and Mullainathan (2004) to evaluate ethnic discrimination in the labor market of Chicago and Boston.

Table 3 shows that of the 70 participants of the experiment, 43 approved the loan application for indigenous men, 40 for non-indigenous men, 64 for indigenous women and 64 for non-indigenous women. Appendix C shows detailed descriptive statistics of the data from the experiment. Next section provides a theoretically-justified model to analyze the

Table 2 Names/surnames used in the experiment

	Names	Surnames
Indigenous male	Juan	Chipana Quispe
Indigenous female	Felipa	Quispe Huanca
Non-indigenous male	Samuel	Gutierrez Espinoza
Non-indigenous female	Pamela	Gomez Gironda

data of loan approval/rejection, taking into account the characteristics of the potential borrower and the characteristics and preferences of the loan officer.

Table 3 Loan approval in the experiment*

		Loan approval	
		No	Yes
Men	Indigenous	27 (39%)	43 (61%)
	Non-indigenous	30 (43%)	40 (57%)
Women	Indigenous	6 (9%)	64 (91%)
	Non-indigenous	6 (9%)	64 (91%)

(*) Frequency of credit applications accepted/rejected from the total of 70 files. In brackets below each frequency: acceptance/rejection rates.

3 Data analysis methods

A logistic mixed-effects model was used to analyze the data of the experiment. Ross S. (2002) pointed out that the decision of approve or deny a loan is ideally suited for discrete choice empirical tools as logit analysis, and this model can be further derived from a utility-maximizing behavior of a credit officer in charge of evaluating a loan application.

Theoretical justification of the logistic mixed-effects logit for the analysis of loan discrimination: Credit officers $\mathcal{C}$ face a choice among $Y = \{R, \neg R\}$ alternatives (reject or not reject a loan application). The utility of $\mathcal{C}$ for alternative y can be expressed as an error-component model,

$$\mathscr{U}_{hy} = \boldsymbol{\alpha}^\top \mathbf{x}_{hy} + \boldsymbol{\mu}_h^\top \mathbf{z}_{hy} + \epsilon_{hy}, \tag{1}$$

where x_{hy} *is a vector of observed variables,* $\mathbf{z}_{hy}$ *is vector of error-components that capture the correlation among alternatives from non-observed random preferences of* $\mathcal{C}$*,* $\boldsymbol{\alpha}$ *is a vector of fixed coefficients,* $\boldsymbol{\mu}$ *is a vector of random terms, and* ϵ_{hy} *is* $i.i.d$ *extreme value. Letting* $\boldsymbol{\beta}^\top = \langle \boldsymbol{\alpha}^\top, \boldsymbol{\mu}_h^\top \rangle$ *and assuming fixed coefficients for variables* x_{hy} *and random coefficients with zero means for variables* $\mathbf{z}_{hy}$*, the utility of equation 1 can be expressed as* $\mathscr{U}_{hy} = \boldsymbol{\beta}_n^\top \mathrm{x}_{hy} + \epsilon_{hy}$*, where the observed variables* x_{hy} *affect the* y *decision of* $\mathcal{C}$*, i.e.* x_{hy} *includes the financial situation and the socio-economic and demographic characteristics of a potential borrower, as well as the characteristics of* $\mathcal{C}$*. The tastes of* $\mathcal{C}$ *are represented by the vector of coefficients* $\boldsymbol{\beta}_h^\top$*, which vary over* $\mathcal{C}$ *in the population with density* $f(\boldsymbol{\beta})$*. Agent* $\mathcal{C}$ *knows the value of his own* $\boldsymbol{\beta}_h$ *and* ϵ_{hy} *and chooses alternative* $\neg R$ $(\neg R \succ R)$ *if and only if* $\mathscr{U}_{h,\neg R} > \mathscr{U}_{h,R}$*. The experiment allows to record* x_{hy} *but not* $\boldsymbol{\beta}_n$ *or* ϵ_{hy}*. In case of an observed* $\boldsymbol{\beta}_h$*, the choice probability would be logistic since* ϵ_{hy} *is* $i.i.d$ *extreme value,*

$$\mathscr{L}_{hy}(\beta_h) = \frac{\exp\left(\mathbf{x}^\top \boldsymbol{\beta}\right)}{1 + \exp\left(\mathbf{x}^\top \boldsymbol{\beta}\right)} \tag{2}$$

As $\boldsymbol{\beta}_h$ *is not observed, the choice probability is the integral of* $\mathscr{L}_{hy}$ *over all possible values of* $\boldsymbol{\beta}_h$*,*

$$\mathscr{P}_{hy} = \int \left(\frac{\exp\left(\mathbf{x}^\top \boldsymbol{\beta}\right)}{1 + \exp\left(\mathbf{x}^T \boldsymbol{\beta}\right)} \right) f(\boldsymbol{\beta}) d\boldsymbol{\beta}, \tag{3}$$

which is the mixed logit probability. See Train (2009).

The logistic mixed-effects model can be estimated with classical (frequentist) methods or with Bayesian methods, see Regier et al. (2009). Under the frequentist paradigm, the null of no effects of ethnicity on loan allocation can be evaluated with conventional procedures as e.g. p-values. The Bayesian approach in experimental economics, suggested by *inter alia* El-Gamal and Palfrey (1996) or Bolton et al. (2003) and used by e.g. Cipriani et al. (2012), allows to measure the *strength of the evidence* in favor or against an hypothesis, in this case the extent to which the data increase or decrease the odds of discrimination during a loan evaluation.

A Bayesian logistic mixed-effects model has the form:

$$\begin{cases} y_{i(h)} | \mathbf{x}_{i(h)} \sim \left(y_{i(h)} | \mathbf{x}_{i(h)} \right), \quad y \in \{0,1\}; \quad i = 1, \ldots, n_h \\ \left(y_{i(h)} | \mathbf{x}_{i(h)} \right) = F^* \left(\mathbf{x}_{i(h)}^\top \boldsymbol{\beta}_{N_h} \right)^y \left[1 - F^* \left(\mathbf{x}_{i(h)}^\top \boldsymbol{\beta}_{N_h} \right) \right]^{y-1} \\ F^* \left(\mathbf{x}^\top \boldsymbol{\beta} \right) = \mathscr{P} \left(Y = 1 | \mathbf{x}^\top \boldsymbol{\beta} \right) = \frac{\exp\left(\mathbf{x}^\top \boldsymbol{\beta}\right)}{1 + \exp\left(\mathbf{x}^\top \boldsymbol{\beta}\right)} \\ \mathbf{x}^\top \boldsymbol{\beta}_{N_h} = \mathbf{x}^\top \boldsymbol{\beta} + u_{0h} \\ \beta_k \sim \mathcal{N}\left(0, v_{\beta_k}\right), \quad k = 1, \ldots, p \\ u_{0h} | \tau_0 \sim \mathcal{N}\left(0, \tau_0\right), \quad h = 1, \ldots, N_h \\ \tau_0 \sim \mathcal{IG}\left(\nu_0, \nu_1\right) \end{cases} \tag{4}$$

In this model, index h indicates group level, n_h is the number of observations in group h, and N_h is the total number of groups. See *inter alia* Gilks et al. (1993), Holmes et al. (2006), Karabatsos (2015) or Masuda and Stone (2015). In the case of the experiment, $y = 1$ ($y = 0$) if the loan application was accepted (rejected) by the credit officer, $h = 1, 2, \ldots, N_h$ for the $N_h = 70$ credit officers that participated in the experiment and $n_h = 4$ since four files were delivered for evaluation to each participant. Precision parameters $\upsilon_{\beta_k} = \tau_0 = \nu_0 = \nu_1 = .1$ around a zero-mean were chosen assuming that no discrimination exists *a priori*. The vector x includes information about the gender of the applicant, the treatment (being indigenous), and the interaction effects among the ethnicity and the gender of the loan applicant, using non-indigenous men as the baseline for comparison. Control covariates were also included in x to account for the characteristics of the participants, the credit profile of the potential borrower, and the financial evaluation of the credit application performed by the credit officers. The inclusion of covariates when analyzing the outcome of an experiment was suggested by e.g. Glennerster and Takavarasha (2013) to reduce unexplained variance; as the control variables were highly correlated, it were summarized into synthetic covariates using multiple correspondence analysis and principal components—see Appendix B for details.

A hybrid Metropolis-Hastings and Gibbs sampling algorithm was used to estimate the Bayesian mixed-effects model, using a Markov Chain Monte Carlo (MCMC) with 32498 iterations, a thin parameter equal to 3 and a burn-in of 2500 samples. Point estimates of β_k were obtained minimizing the expected loss of a squared-error function, i.e. the Bayesian point-estimators are the mean of the posterior distribution of β_k, see Gill (2014).

Define $\mathbb{e}$ as the Napier's (Euler's) constant. Odds ratios calculated with $\mathbb{e}^{\beta_k}$ were used to measure the association between the exposure and the outcome of the experiment, due to its convenient interpretation: if $\mathbb{e}^{\beta_k} = 1$, there will be no relationship between loan approval and the ethnicity/gender of the potential borrower, but if $\mathbb{e}^{\beta_k} > 1$ ($\mathbb{e}^{\beta_k} < 1$) the exposure will be associated with higher (lower) odds of loan approval; see Bland and Altman (2000) or Szumilas (2010).

4 Results

Frequentist Analysis. Table 4 shows the maximum likelihood estimation of the mixed-effects logistic regression. Multicollinearity prevented the estimation of the interaction effects of ethnicity/gender on credit lending for indigenous women and indigenous men. The null of no effects of ethnicity or gender on loan approval cannot be rejected at conventional significance levels using this technique. The null of a logit model without mixed-effects was rejected with a significance level of less than 1% using a likelihood ratio test, and the estimated intraclass correlation among the participants of the experiment was .7951, with a 95% confidence interval of .5073 to .9360; these last results support the use of a mixed-effects logit model to analyze the data of the experiment.

Table 4 Mixed-effects logistic regression of loan approval: frequentist estimation

	Odds ratio	95% Confidence interval		z-stat	p-value
Ethnicity	1.53	0.35	6.76	0.56	0.577
Gender	5.44E+07	2.1E-07	1.5E+22	1.05	0.293
Interaction effects					-
Non-indigenous women	1.71	0.08	37.29	0.34	0.732
Indigenous women	-	-	-	-	-
Indigenous men	-	-	-	-	-
	Estimate	95% Confidence interval			
Random-effects parameter	1.89	1.36	2.63		

Bayesian Analysis. Table 5 and Figures 3 and 4 show the results of estimating the mixed-effects model with Bayesian methods. Good convergence and well-mixing of the MCMC chains was observed in the runs: the trajectory of the chains is stable over time in the trace plots (Figures 3 and 4, left), the efficiency rates of the parameters are above 15%, and the Geweke's convergence diagnostic (Geweke, 1991) suggests that the chains are stationary (Table 5).

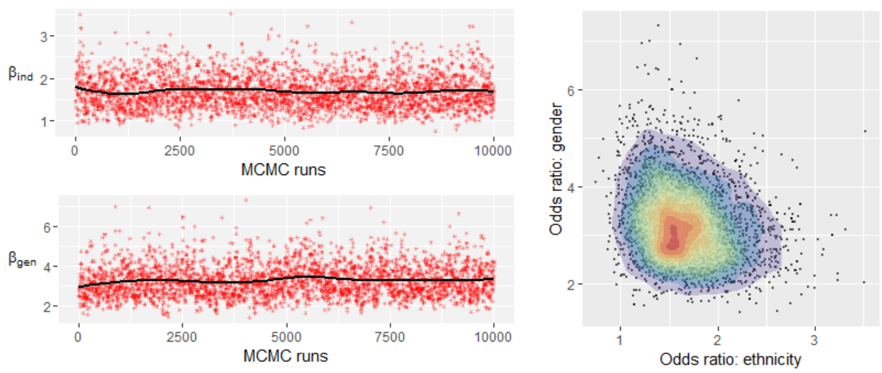


Fig. 3 Bayesian estimation of treatment effects. β_{ind}: association between ethnicity and credit lending, β_{gend}: association between gender and credit lending.

The results of the Bayesian estimation suggest that, with a 95% probability, the combined gender and ethnic characteristics of a borrower are important for credit approval. Point estimates of the odds ratios—conditional on the data and the assumptions of the experiment—, suggest that

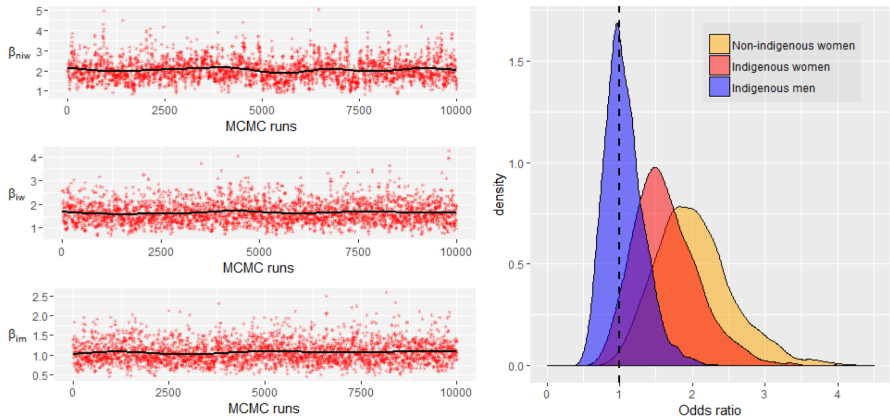


Fig. 4 Bayesian estimation of interaction effects. β_{niw}: odds of credit lending for non-indigenous women, β_{iw}: odds of credit lending for indigenous women, β_{im}: odds of credit lending for non-indigenous men

Table 5 Mixed-effects logistic regression of loan approval: Bayesian estimation

	Odds ratio	95% Credible interval		Efficiency	Geweke
Ethnicity	1.63	1.04	2.58	0.536	0.412
Gender	3.17	2.01	5.04	0.310	-1.506
Interaction effects					
Non-indigenous women	1.97	1.16	3.24	0.171	-0.111
Indigenous women	1.58	0.92	2.69	0.372	-1.658
Indigenous men	1.04	0.64	1.71	0.453	-1.072
	Estimate	95% Credible interval			
Random-effects parameter	1.22	.77	1.73		

non-indigenous women have twice the chances of receiving a credit compared to non-indigenous men. Indigenous women in turn have 1.5 more chances of receiving a credit compared to non-indigenous men. No difference is observed in the chances of receiving a loan between indigenous and non-indigenous men: the 95% credible interval for the interaction effect of indigenous men is between .64 and 1.71.

Figure 3 (right) shows the interaction of the parameters of gender and ethnicity: even if both variables jointly affect the chances of receiving a loan, the uppermost effect is caused by gender—specifically by been a woman. Figure 4 (right) shows that the odds ratio density for indigenous women $f_{iw}\left(\mathrm{e}^{\beta}\right)$ crosses zero with a 95% probability, but its between 1 and 2.48 with a 90% probability. An overlapping region between $f_{iw}\left(\mathrm{e}^{\beta}\right)$ and the odds density of non-indigenous women $f_{niw}\left(\mathrm{e}^{\beta}\right)$ is observed. A non-parametric estimation of this overlapping region (Schmid and Schmidt, 2006),

$$\int_{-\infty}^{+\infty} \min\{f_{iw}\left(\mathbb{e}^{\beta}\right) f_{niw}\left(\mathbb{e}^{\beta}\right)\} d\mathbb{e}^{\beta} \approx .68,$$

suggests that, even if women have higher odds of loan approval in terms of point estimates, the difference between indigenous and non-indigenous women may be negligible based on intervallic results.

5 Discussion

Evidence of favorable loan discrimination for women was found after performing a field experiment of credit allocation in a controlled laboratory setting, with real credit officers. This result may seem counterintuitive to the general evidence of gender gaps in credit lending [4], but it is in fact consistent with the *micro* credit model of lending: following the original model of Grameen Bank, female micro-credit borrowers were targeted by other micro-finance organizations like BancoSol and non-Governmental Organisations (NGOs) as ProMujer, both institutions currently working in Bolivia, where the experiment take place[5]. The findings of the experiment are also congruent with the general equilibrium model of credit market discrimination of Han (2004), where taste-based discrimination arise if loans to minority borrowers have lower expected rates of default loss, i.e. if the participants of the experiment believed that the expected loan performance of women is better than those of men, a preference for women may have arisen. This could be the case since Maclean (2010) —through an ethnographic study performed in La Paz, Bolivia— found that

[4] Cross-country studies have found that women are less likely to use credit (Demirgüç-Kunt et al., 2013), female-managed firms are less likely to obtain a bank loan compared with male-managed counterparts (Muravyev et al., 2009), or female-owned firms have a lower probability of access to credit (Calcagnini et al., 2015). Mixed-evidence of this gender gap was found for Latin American countries: Bruhn (2009) did not found systematic evidence of gender discrimination, while Piras et al. (2013) found that women-led businesses are more likely to be financially constrained than other comparable firms, with a gender gap driven by taste-based discrimination, and Agier and Szafarz (2013) did not found a gender bias in loan denial in Brazil, but rather a gender gap in loan size. The results of the experiment are similar to those of Asiedu et al. (2012), who found that black-owned and hispanic-owned firms faced more discrimination in obtaining credit but in contrast white women firms did not face discrimination in terms of access to loans, and in fact paid a lower interest rate than white male firms.

[5] Mayoux (2000) explained the preference of the micro-credit model for women by three paradigms: (*i*) financial self-sustainability, (*ii*) poverty alleviation, and (*iii*) women empowerment. The first paradigm targets women because of efficiency considerations, i.e. high female repayment rates and contribution of women's economic activity to economic growth. The second paradigm targets women because of higher levels of female poverty and women's responsibility for household well-being. Finally, if micro-finance is conceived as an entry point for women's economic, social and political empowerment, women are targeted due to gender equality and human rights considerations. Armendáriz and Morduch (2010) added that micro-finance is focused on self-employed small businesses in the informal sector, typically controlled by women, and Aggarwal et al. (2015) further argued that microfinance institutions will focus on women in an environment of lower social trust.

women use their social networks as a source of founding to repay their debts. This cultural collateral could be recognized by loan officers as an additional guarantee of loan repayment. Gender identity may have also play a role in the results, if female loan officers better appreciate the ability of female entrepreneurs in terms of completing their project and/or repaying the debt (Beck et al., 2011). It is evident in any case that the granting decision is based on subjective judgment of loan officers drawing from previous experience (Baklouti and Baccar, 2013) and nonquantifiable data (Wilson, 2015), creating room for discrimination and explaining why different bank officials can reach different conclusions on the same loan proposal[6].

In the case of the effects of ethnicity on micro credit allocation, the results are inconclusive. While some evidence of a preference on credit lending for non-indigenous women over indigenous women was found, further research is needed to properly unravel the existence of ethnic-related discrimination. This issue is particularly relevant in Bolivia, where almost half of the total population (49%) identifies itself as indigenous or part of an ethnic community, according to the last census of Bolivia from 2012. The lack of conclusive evidence about ethnic barriers in credit access does not imply the absence of discriminatory practices in the credit market: as with other experiments, external validity is limited by the heterogeneity of the population in Bolivia, making impossible to generalize the results to other ethnic groups different from the Aymara nation, and it is possible that a social desirability bias make the loan officers hide their true preferences about ethnic minorities. Moreover, the experiment only analyzed credit access, and it possible that discrimination exists in other stages of the loan allocation process, i.e. discrimination may exist not only in credit rejection rates but also in terms of predatory lending, which implies that indigenous individuals and low-income borrowers are obtaining loans at high interest rates and unfavorable terms. Also, in developing countries like Bolivia, geographical discrimination can arise if low-income indigenous communities are disproportionately found in locations that lack of financial services[7].

[6] Arya et al. (2013) showed that subjective aspects as trustworthiness are important for credit scores, due to the difference between the ability to pay a debt and the willingness to pay, the last one related to factors different from economic and financial capabilities. In terms of ethnic effects in trustworthiness, Karlan (2005) found a differences in social capital and financial decisions between pairs of indigenous and pairs of non-indigenous groups, applying an experimental trust game in Ayacucho, a village of Peru.

[7] Structural barriers to financial inclusion may also affect credit allocation for indigenous women, (*i*) if the economic activity of non-indigenous female-owned firms is less capital intensive than those of indigenous female-owned firms, (*ii*) if the ethnicity of the credit officer affects loan approval, i.e. if loan officers favor in-group over out-group members, and (*iii*) if indigenous females have lower financial literacy rates or experience language barriers. In Bolivia, Tassi et al. (2012) further found that popular Aymara entrepreneurs developed their own strategies for trading based on their culture, i.e. based on its own history and its own forms of relationship, due to the exclusion from the formal economy, the discrimination from the 'dominant bourgeoisie'—as called byTassi et al. (2012)—and their limited social mobility.

Since individuals without access to credit are denied the chance of self-employment and economic opportunities that are important for empowerment and for breaking the cycle of inter-generational poverty (McDonnell et al., 2001), it is important to keep evaluating the existence of credit discrimination, particularly in the case of indigenous women with comparable credit background to that of non-indigenous women, as financial access based upon collective organization can reinforce women's vision of identity—see Lazar (2004).

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Appendix A: Theoretical models of discrimination in credit markets and empirical evidence for the lab-field experiment in Bolivia

Two main competitive theoretical models of discrimination exist: taste-based discrimination (henceforth, TBD) and statistical discrimination (SD). TBD was originally proposed by Becker (2010) as an intrinsic unpleasantness against members of a group, which results from ignorance or prejudices attached to ethnic and/or gender characteristics. Becker (2010) showed theoretically that taste-based discrimination —because of race, religion, sex, color, social class, personality, or other non-pecuniary considerations— originates a misallocation of resources, ultimately reducing real incomes in the market, particularly those of the minority who was discriminated. Extensions of TBD for credit markets can be found in Dymski (1995) or Han (2004).

Statistical discrimination is based on the work of Arrow (1973) and Phelps (1972). SD is theoretically a result of incomplete information: when there is a need to make choices under uncertainty, decision-makers appeal to prior information about the qualities of a group based on (*i*) sociological beliefs or (*ii*) previous statistical experience about the default rates of the minority group. The discriminatory decision can be considered rational —in the maximizing-expected-utility sense— if the cost of acquiring information is sufficiently high. In this case, credit officers will draw upon easily observable characteristics of a group —like gender and ethnicity— as a proxy for the payment capacity of the potential borrower, if these characteristics are correlated with the performance of the borrowers, and loan approval choices will be affected even if the credit officer does not have an intrinsic (taste-based) prejudice against the minority group. See *inter alia* Scalera and Zazzaro (2001).

To understand the nature of discrimination in the experiment, two exercises with the participants were performed:

1. In the first excercise, participants were asked to sort the credit applications files according to the order of revision they will follow during the experiment. In this exercise, discrimination, if any, can be caused by TBD or SD: TBD can arise by an intrinsic unpleasantness of a credit officer against the file of a potential borrower, while SD can arise as a result of the short time provided to decide the revision order of the applications, i.e. as there was no enough information to decide about the applications, credit officers may have use the ethnicity/gender of the potential borrower as a proxy for the payment capacity of the applicant.

   Table 6 shows the number of times that a specific credit application file was preferred for revision. A higher proportion of indigenous men applications and non-indigenous women applications (37% and 29%, respectively) were selected first for revision, compared to indigenous women (21%) and non-indigenous men (13%). It is unclear whether this selection is caused by TBD or SD or whether to be selected first for revision is a favorable or unfavorable for credit lending.

Table 6 Number of credit applications preferred for revision

Gender/ethnicity	Indigenous	Non-indigenous	Marginal (gender)
Male	41	15	56
Female	24	32	56
Marginal (ethnicity)	65	47	

2. In the second exercise, performed after all of the information was analyzed by the credit officers, the participants were asked to sort the credit applications according to their preferences in loan disbursement for each client. The second exercise was designed to reduce the motivation for SD, since the participants had access and time to evaluate the complete information of the potential borrower; thus, any remaining discrimination in the sorting of files should only be related to TBD.

Table 7 shows the preferences in loan disbursement for the second exercise. In this case there is a slight preference of disbursement for non-indigenous women (30%) and indigenous women (28%) over indigenous men (25%) and particularly over non-indigenous men (16%).

Table 7 Number of credit applications preferred for loan disbursement

Gender/ethnicity	Indigenous	Non-indigenous	Marginal (gender)
Male	20	13	33
Female	22	24	46
Marginal (ethnicity)	42	37	

The statistical hypothesis of no differences in these proportions can be evaluated estimating the probability of preferences in loan disbursement by gender/ethnicity using a conjugate Beta-Binomial model. Let f_1 be an observed frequency with a marginal n_1 that will be compared with another frequency f_2 with n_2 from Table 7, if

$$f_1 \sim \text{Binom}(n_1, \theta_1), \text{and} \tag{5}$$

$$f_2 \sim \text{Binom}(n_2, \theta_2), \tag{6}$$

with the proportions $\theta_1 \in [0,1]$, $\theta_2 \in [0,1]$, which follow a Beta distribution $\theta_1 \sim \mathcal{B}(1\text{E}10^2, 1\text{E}10^2)$, $\theta_2 \sim \mathcal{B}(1\text{E}10^2, 1\text{E}10^2)$ centered on an equiprobability of .5 (i.e. the Laplace's principle of indifference), then,

$$p(\theta_1|f_1, n_1) \sim \mathcal{B}(\theta_1|y_1 + 1\text{E}10^2, n_1 - y_1 + 1\text{E}10^2), \tag{7}$$

$$p(\theta_2|f_2, n_2) \sim \mathcal{B}(\theta_2|y_2 + 1\text{E}10^2, n_2 - y_2 + 1\text{E}10^2), \tag{8}$$

and the probability of preferences in loan disbursement can be calculated with the density of $\delta = \theta_1 - \theta_2$, computed by solving the integral,

$$p(\delta|f,n) = \int_0^\infty \mathcal{B}(\theta|y_1 + 1\text{E}10^2, n_1 - y_1 + 1\text{E}10^2)\mathcal{B}(\theta - \delta|y_2 + 1\text{E}10^2, n_2 - y_2 + 1\text{E}10^2)d\theta, \quad (9)$$

analytically or with a Monte Carlo approximation. Table 8 shows the results of a Monte Carlo simulation used to approximate the integral in equation 9. On average, a clear preference in loan disbursement is observed for non-indigenous women —a result which coincides with those of the mixed-effects logistic model— when compared to non-indigenous men and to a lesser extent when compared to indigenous men and indigenous women. This last result could be interpreted as evidence of taste-based discrimination in credit lending favorable for non-indigenous women.

Table 8 Preferences in loan disbursement: Probability and average probability

Treatment	Preference	Probability	Average
Non-indigenous female (Fni)	Fni ≻ Fi	0.66	0.68
	Fni ≻ Mi	0.73	
	Fni ≻ Mni	0.66	
Indigenous female (Fi)	Fi ≻ Fni	0.34	0.47
	Fi ≻ Mi	0.34	
	Fi ≻ Mni	0.72	
Non-indigenous male (Mni)	Mni ≻ Mi	0.34	0.32
	Mni ≻ Fi	0.28	
	Mni ≻ Fni	0.34	
Indigenous male (Mi)	Mi ≻ Mni	0.66	0.53
	Mi ≻ Fi	0.66	
	Mi ≻ Fni	0.27	

Appendix B: Synthetic covariates

Synthetic control covariates were included in the mixed-effects logistic model to account for (*i*) the characteristics of the participants, (*ii*) the credit profile of the potential borrower, and (*iii*) the financial evaluation of the credit application performed by the credit officers. The data of the experiment was summarized into these synthetic covariates using multiple correspondence analysis (MCA), when the data was nominal or ordinal, and with principal components (PCA) when the data was continuous (Table 9). See Francois Husson (2010) for details on these techniques.

Table 9 Synthetic control covariates

Experimental data	Type	Synthetic Covariate	Method
Rate of the payment capacity	Ordinal	Evaluation of the loan application made by the credit officer	MCA
Rate of the business experience	Ordinal		
Rate of the quality of the guarantor	Ordinal		
Amount requested vs. financial needs	Nominal		
Trustfulness of the potential borrower	Ordinal		
Modification of the loan amount	Nominal		
Loan amount requested	Continuous	Credit profile of the potential borrower	PCA
Household expenses	Continuous		
Assets of the potential borrower	Continuous		
Monthly payment fee of the loan	Continuous		
Collateral's final cash balance	Continuous		
Collateral's financial wealth	Continuous		
Final cash flow of the client's business	Continous		
Average sales of the client's business	Continous		
Gender of the credit officer	Nominal	Characteristics of the credit officer	MCA
Years of experience in micro-finance	Ordinal		
Years of experience as credit officer	Ordinal		
Education	Ordinal		
Marital status	Nominal		
Financial institution of the credit officer	Nominal		

Appendix C: Descriptive results

Frequencies of the data collected with the evaluation sheet of the experiment are shown in Table 10. The frequencies are displayed according to the gender/ethnicity of the application folder.

Table 10 Descriptive results of the experiment*

Variable	Categories	Fni	Fi	Mni	Mi
Loan approval	No	6	6	30	27
	Yes	64	64	40	43
	Total	70	70	70	70
Revision order	First	6	11	22	31
	Second	9	11	28	22
	Third	28	22	8	12
	Fourth	27	26	12	5
	Total	70	70	70	70
Disbursement order	No preference	28	27	43	38
	First	15	19	1	9
	Second	20	14	7	3
	Third	6	5	6	17
	Fourth	1	5	13	3
	Total	70	70	70	70
Payment capacity	Very bad	0	0	1	1
	Bad	5	11	20	17
	Good	57	54	48	51
	Very good	8	5	1	1
	Total	70	70	70	70
Client's experience	Very bad	1	0	1	1
	Bad	3	3	3	4
	Good	59	60	63	65
	Very good	7	7	3	0
	Total	70	70	70	70
Collateral	Very bad	2	0	3	1
	Bad	3	3	7	8
	Good	36	43	51	45
	Very good	29	24	9	16
	Total	70	70	70	70
Client's trustfulness	Completely reliable	4	5	2	2
	Reliable	47	48	26	30
	Unreliable	19	17	36	35
	Not trustworthy			6	3
	Total	70	70	70	70
Loan amount answers the necessities of the client's business	No	8	7	41	37
	Yes	62	63	29	33
	Total	70	70	70	70
Perceived chance of default	Average	23.93	23.78	43.43	40.78

(*) Fni: non-indigenous female, Fi: indigenous female, Mni: non-indigenous male, Mi: indigenous male.