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SPECIAL SYMPOSIUM: PROMOTING YOUTH AND FEMALE ENTREPRENEURSHIP IN DEVELOPING COUNTRIES

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The interaction effect of gender and ethnicity in loan approval: A Bayesian estimation with data from a laboratory field experiment

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Abstract

Microfinance targets women and uses loan provision as a tool for empowerment, which translates into better household nutrition, improved education, and a scale down of domestic violence. However, ethnic discrimination in microfinance may exist in countries with a segregated indigenous population. We assessed this possibility with a field experiment in Bolivia. The controlled laboratory experiment evaluated whether credit officers rejected microloan applications based on the interaction effect of ethnicity and gender of potential borrowers. Point estimates of a Bayesian mixed-effects logistic regression, estimated with the experimental data, indicate that nonindigenous women have double the chance of loan approval, but indigenous women have only 1.5 times the chance of loan approval when compared with men. While the findings about gender are limited, the evidence for the interaction of gender and ethnicity is more robust and suggests the existence of positive taste-based discrimination favorable for nonethnic women in Bolivia. We conclude that the affirmative actions towards women promoted by development agencies and microfinance institutions must not overlook ethnicity as an important factor for financial policies of sustainable development. In practice, these policies should be aimed at identifying and reducing both social desirability bias and the structural barriers to financial inclusion that indigenous women may face when trying to obtain access to a loan.

KEYWORDS
credit access, gender gaps, indigenous peoples, discrete choice, Bayesian analysis

JEL CLASSIFICATION
G21; J15; C25; C11

1 | INTRODUCTION

Microfinance institutions (MFIs) tend to shows preferences in loan disbursement for women. Following the original model of Grameen Bank, in Bolivia female microcredit borrowers are targeted by microfinance organizations such as BancoSol and nongovernmental organizations (NGOs) such as ProMujer.

Abbink, Irlenbusch, and Renner (2006) explain that microfinance organizations target women because these institutions see women's empowerment as a goal but also because women are often seen as more reliable borrowers. Rasmussen (2012) relates the gender focus to women's economic resilience, since savings enable women to handle income shocks and confront unforeseen emergencies such as illness or loss of employment (Ghosh & Vinod, 2017). Guha and Gupta (2005) add that the main reason of microfinance for targeting women over men is based on the premise that women make a higher contribution to family welfare, since women give priority to spending their earnings on their children, thus helping to improve nutrition and reduce child mortality.

In Bolivia, despite the efforts to reduce discrimination and eliminate barriers in the credit market[1], discriminatory practices limiting the access to financial services for women from ethnic groups may still exist. According to World Bank (2015), in Bolivia, extreme poverty for people belonging to indigenous groups in rural areas is still twice that of nonindigenous people—51.6% compared with 22.5%—and 64% of the household heads in extreme poor households were indigenous, compared to 22% of the nonpoor household heads. Lundvall, Garriga, Bonfert, Tas, and Villegas-Otero (2015) add that women who belong to indigenous groups in Bolivia have lower education outcomes than any other group. For example, the literacy rate for indigenous women is 15 percentage points lower compared with nonindigenous men, creating a structural barrier for financial access.

Gender and ethnicity are thus relevant issues to focus on when analyzing financial inclusion, since both could be a source of discrimination in credit access. While gender is recorded when applying for a loan, there are no records of ethnicity in credit scoring (since this would be a discriminatory practice itself) and thus it is not possible to use administrative information from financial institutions to assess the extent of discriminatory practices during loan provision. Nevertheless, a laboratory–field experiment can be performed to evaluate if ethnic/gender discrimination is a barrier limiting access to financial services for micro and small entrepreneurs.

This study presents the results of a laboratory–field experiment carried out to test the existence of loan discrimination for ethnic women in the credit markets of the cities of La Paz and El Alto in

Bolivia. The study contributes to the literature regarding controlled experiments for discrimination since, to our knowledge, ethnic discrimination in credit markets of developing economies has never been analyzed before by means of an economic lab–field experiment.

In the experiment, similar credit files were delivered to 70 real credit officers from six microfinance institutions (MFIs) in order to see if the outcomes—rejection or approval of the loan application—were different depending on the ethnicity/gender of the applicant. The results of the study were obtained with a Bayesian mixed-effects logistic regression estimated with the data of the experiment. The findings show higher probabilities of preference in loan disbursement—congruent with taste-based discrimination—for nonindigenous women. The findings suggest that (i) nonindigenous women have twice the chance of obtaining credit compared with nonindigenous men, (ii) indigenous women have 1.5 times more chances of obtaining credit compared with nonindigenous men, and (iii) there is no difference between indigenous and nonindigenous men in the chances of obtaining a loan.

While the findings are not totally conclusive about gender, the results do highlight the existence of an interaction effect between gender and ethnicity, that is, a preference for nonindigenous women when providing a loan. This last result is not surprising, given the fact that according to Li, Gan, and Hu (2011) microfinance is often targeted at women and is used as a tool to empower women for two main reasons: first, microfinance releases women from performing domestic tasks, thus moving them from the household to the sector of income-generating activities in the wider-community economics. Secondly, given the fact that poor women earn different income from those obtained by their spouses, through microfinance women can support their families and increase their self-esteem. Also, according Shaheen, Hussain, and Mujtaba (2018), women economically empowered raise the welfare of their families, by improving the education and nutrition of their children, and by reducing the options of women and their children to suffer from violent situations.[2] Despite the well-known and documented preferences for women in microfinance, the results of this study suggest nonetheless that the affirmative actions towards women promoted by development agencies and microfinance institutions have to take into consideration ethnicity as an additional factor for policies of financial inclusion, particularly in countries with a historically segregated indigenous population.

The rest of the study is structured as follows: a brief literature review can be found in Section 2. Section 3 explains the experimental design and Section 4 describes the methods of data analysis. Section 5 explains the results and Section 6 concludes. The data from the experiment and the computer codes to replicate the results are available upon request.

2 | LITERATURE REVIEW

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, despite having similar characteristics.

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 nonpecuniary considerations—results in a misallocation of resources, ultimately reducing real incomes in the market, particularly those of the minority who experience the discrimination. Extensions of TBD for credit markets can be found in Dymski (1995) and Han (2004). Statistical discrimination is based on the work of Arrow (1973) and Phelps (1972). Theoretically, SD is 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, such as 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. Furthermore, 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).

Field experiments on discrimination tend to be focused on correspondence studies for labor markets in developed economies—see Rich (2014), and 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 red-lining, mortgage loan data, and audit (in-person) studies. Studies based on observational data, such as Deku and Kara (2013), found evidence that households of a racial origin other than white were more likely to be excluded from consumer credit in the United Kingdom, while Blanchflower, Levine, and Zimmerman (2003) found that black-owned small businesses were almost three times more likely to have a loan application denied in the U.S. small business credit market. However, Nwosu, Orji, Nnetu, and Nwangwu (2015), using observational data from a developing country, did not find significant discrimination against women entrepreneurs in the formal credit markets of Nigeria, after analyzing the enterprise survey data of this country from 2010. Other studies, such as Pope and Sydnor (2011), found that in peer-to-peer credit markets (prosper.com) loan listings with blacks in the attached picture were 25% to 35% less likely to receive funding than those of whites with similar credit profiles; using also photographs of potential borrowers from prosper.com, Duarte, Siegel, and Young (2012) further showed that borrowers who appeared more trustworthy had higher probabilities of having their loans funded, a finding that is consistent with the trust-intensive nature of lending.

In terms of audit studies, Turner et al. (2002) matched Hispanic and African-American testers with white testers, who had roughly equivalent financial backgrounds, to evaluate discriminatory treatment when they inquired about loan products. Their results showed that most people of color did not face discriminatory treatment when they inquired about loan products, but in contrast African-American and Hispanic homebuyers faced a statistically significant risk of receiving less favorable treatment than whites did when they asked 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. They found that there was a significant difference in the probability of being granted a loan in favor of the male applicant if the university qualification was absent. 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. Results showed that black men and white women were more disadvantaged relative to black women and white men in their experimental credit market.

Cross-country studies have found that women are less likely to use credit (Demirgüç-Kunt, Klapper, & Singer, 2013), female-managed firms are less likely to obtain a bank loan compared with male-managed counterparts (Muravyev, Talavera, & Schäfer, 2009), and that female-owned firms have a lower probability of access to credit (Calcagnini, Giombini, & Lenti, 2015). Mixed evidence of this gender gap was found for Latin American countries: Bruhn (2009) did not find systematic evidence of gender discrimination, while Piras, Presbitero, and Rabellotti (2013) found that women-led businesses were more likely to be financially constrained than other comparable firms, with a gender gap driven by taste-based discrimination, and Agier and Szafarz (2013a) did not find a gender bias in loan denial in Brazil, but rather a gender gap in loan size. The preference of the microcredit model for women was explained by Mayoux (2000) through three paradigms: (i) financial self-sustainability, (ii) poverty alleviation, and (iii) women's empowerment. The first paradigm targets women because of efficiency considerations; that is, high female repayment rates and the 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 microfinance is conceived as an entry point for women's economic, social and political empowerment, women are targeted owing to gender equality and human rights considerations. Armendáriz and Morduch (2010) added that microfinance is focused on self-employed small businesses in the informal sector, typically controlled by women, and Aggarwal, Goodell, and Selleck (2015) further argued that microfinance institutions will focus on women in an environment of lower social trust.

3 | EXPERIMENTAL DESIGN

The experiment was designed to evaluate whether real credit officers reject microloan applications based on the ethnicity/gender of potential borrowers. 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 & List, 2009).

3.1 | Recruitment of participants

Meetings with the executive directors of six MFIs from Bolivia were held to recruit credit officers for the experiment. Following the instructions of the research team, each MFI sorted its list of credit officers working in the cities of La Paz and El Alto in alphabetical order and then provided the names and contact information of the first 10 and the last 10 credit analysts from the list. These cities were chosen because both are highly populated by credit officers who were close to the site where the experiment took place[3]. The contact with every credit officer was performed by phone calls and through e-mails attached with an invitation letter. Eighty-six credit officers accepted the invitation to participate in the experiment.

3.2 | 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 study was that credit officers translated 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, as they correctly approved credit files with good financial indicators. However, when they were asked about allocating a (continuous) probability of default to the same files, they wrongly choose high probabilities for approved files, which is a counterintuitive appreciation of the concept of default probability. Thus, a dichotomic variable (rejection or approval of a loan application) was chosen as the outcome of the experiment.

3.3 | Lab–field experiment

The lab–field experiment was conducted from March 5 to March 12, 2016 at the Catholic University of San Pablo in the city of La Paz. An attendance rate of 81% was observed: 70 credit officers of the 86 that accepted the invitation actually attended and participated in the experiment. Even if participants were allowed to abandon the activity at any time, all participants stayed until the end of the experiment (see Figure 1). At the end of the evaluation, each participant received approximately U.S.$36.00 as a payment for their participation.

3.4 | Experimental procedures

In the first step of the experiment credit officers completed a registration form to obtain demographic information about the participants. Afterwards, a team researcher explained the purpose of the activity to the participants, the payment they would receive and the procedure. Four application files were then delivered to each of the participants. Once all of the participants had received their files, they were required to state the order in which they wanted to evaluate their four applications. They had two minutes to decide this order, which was timed using a stopwatch. Then, participants were asked to evaluate each loan application and answer questions on a loan evaluation sheet (Figure A1 in the Appendix). After one hour of studying their files, participants were interrupted and they were asked to order the files again, this time in relation to the loan release order they preferred, if any. In the last step of the experiment the research team validated the participants' evaluations to avoid missing values. The ordering of the activities of the experiment was aimed at disentangling taste-based discrimination from statistical discrimination.

3.5 | 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 were informed that the experiment was focused on improving the understanding about the process of credit evaluation in MFIs. In order to avoid biased attitudes caused by a Hawthorne effect, participants did not know the real purpose of the experiment (discriminatory behavior in credit lending).

3.6 | 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 nonindigenous male, a loan application from an indigenous female and a loan application from a nonindigenous female. The

FIGURE 1 Lab–field experiment [Colour figure can be viewed at wileyonlinelibrary.com]

information in 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 (spouse or cohabiting partner) 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 shows that the information of the four credit files provided to the credit officers was similar but not identical. To further ensure that the information was balanced between application files and to isolate its effect on the experiment, indigenous and nonindigenous names and surnames and the pictures (the treatment) were swapped between files for each category of information I, II, III, IV, both for men (I, II) and women (III, IV).

3.7 | Treatment design

Pictures and indigenous-sounding surnames of potential borrowers were used as the treatment of the experiment. In Bolivia, surnames of potential borrowers signal ethnicity, while photos convey further additional information to credit officers about ethnic belonging, since the appearance of individuals from the Aymara ethnic group in Bolivia is highly distinctive.

In relation to surnames, Rodriguez-Larralde et al. (2011) found a correlation between the frequency of indigenous surnames and the high altitude above sea level of the regions in Bolivia, suggesting that in cities of high altitude such as La Paz and El Alto, where the experiment took place, surnames can provide a signal for ethnicity of the borrower. Pictures, in turn, were passport-like and were chosen considering indigenous and nonindigenous physical characteristics of potential borrowers between 30 and 45 years old. In the pictures, the skin tone of indigenous potential borrowers is darker compared with those of the control group, and the face shape of the indigenous borrowers—slanted eyes and prominent cheekbones—are typical of the Aymara nation, an ethnic group of the Andes and Altiplano regions of South America (see Buechler & Buechler, 1971).

Among these characteristics, the darker skin color is probably the most important signal of ethnicity, since as noted by Telles, Flores, and Urrea-Giraldo (2015), in Latin America there is as an ethnic hierarchy based on a color continuum with whites on top, indigenous and black people at the bottom, and mestizos in the middle. For ethical reasons we cannot include the pictures used in the experiment, in order to preserve the anonymity of the volunteers who agreed to provide their pictures for the purpose of the study. Nonetheless the pictures are available upon request for interested researchers.

TABLE 1 Loan application information (in U.S. dollars)

	Credit file			
Information	**I**	**II**	**III**	**IV**
Assets	3,947	4,085	8,248	8,237
Amount requested	1,020	1,050	1,312	1,341
Sales income	1,254	1,254	1,749	1,778
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	58,855	58,841	53,724	53,659

Candidate names were selected based on the most frequent names from the official list of voters elaborated by the Organismo Electoral Plurinacional (Electoral Organism of Bolivia). In order to decide which names were indigenous and which were not, an online survey applied to a nonprobabilistic 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 nonindigenous and four of these names and surnames were used in the experiment (see 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 in the experiment, 43 approved the loan application for indigenous men, 40 for nonindigenous men, 64 for indigenous women, and 64 for nonindigenous women. Table 4 shows detailed descriptive statistics of the data collected with the evaluation sheet of the experiment. The frequencies are displayed according to the gender/ethnicity of the application folder.

4 | METHODS OF DATA ANALYSIS

A logit mixed-effects model was used to analyze the data from the experiment. A logit model uses a logistic function to model a binary dependent variable. In this case the dependent variable is the decision to accept or reject a loan to a potential borrower, decided by the credit officer who was part of the experiment.

TABLE 2 Names/surnames used in the experiment

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

TABLE 3 Loan approval in the experiment

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

Note: Frequency of credit applications accepted/rejected from the total of 70 files. In parentheses below each frequency: acceptance/rejection rates.

TABLE 4 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

Note: Fni, nonindigenous female; Fi, indigenous female; Mni, nonindigenous male; Mi, indigenous male.

The logistic model is mixed because it takes into account both the main effects of interest—ethnicity and gender of the potential borrower—and also fixed effects of the loan-application folders evaluated by each credit officer. A similar methodology with logistic models was used by Coyne, Isaacs, and Schwartz (2010) to evaluate taste-based discrimination in entrepreneurship, and also by Labie, Méon, Mersland, and Szafarz (2015), who used logit models to evaluate the discrimination of microcredit officers against potential borrowers with disabilities in Uganda.

The variables that measure the main effects of interest in the regression are (i) the gender of the applicant, (ii) the ethnicity of the applicant, and (iii) the interaction among ethnicity and gender. Besides the main effects of interest, control covariates were included in the model to account for potential imbalances between the control and the treatment group. These imbalances arise from the fact that the credit profiles tend to be favorable for women in terms of assets of collateral, since the objective of the experiment was testing ethnic discrimination and thus the experimental design focused on balancing the folders of indigenous potential borrowers against nonindigenous potential borrowers.

The control covariates included in the regressions were the payment capacity of the applicant, the business experience of the applicant, the quality of the guarantor, the amount requested, the financial needs of the business, the trustfulness of the potential borrower, a potential modification of the loan amount, household expenses, the assets of the potential borrower, the monthly payment fee of the loan, the collateral's final cash balance and financial wealth, the cash flow of the business, the average sales of the business, the gender of the credit officer, the years of experience in microfinance of the credit officer, and the education, marital status, and financial institution of the credit officer. Because of the large number of control covariates, these variables were reduced to the most important factors using principal component analysis (PCA) for continuous variables and multiple correspondence analysis (MCA) for categorical variables. These techniques synthesize the variables into factors that account for the main characteristics of the credit profile of the potential borrower and the financial evaluation of the credit application performed by the credit officers (see Table 5).

The logit model also included cluster fixed effects for credit folders, because each credit officer received four folders for evaluation and so that it was possible for the results of evaluating the folders to be correlated for each officer. The model was estimated with traditional (frequentist) methods and also with Bayesian methods. Bayesian methods were used to avoid the problems of multicollinearity in the frequentist estimation with maximum likelihood. See Section A3 in the Appendix for details about the methodology used in the study.

5 | RESULTS

5.1 | Frequentist analysis

Table 6 shows the maximum likelihood estimation of the mixed-effects logistic regression. The use of mixed-effects models was supported by the empirical estimation because the null of no mixed effects was rejected with a significance level of less than 1% using a likelihood ratio test[4]. "Nonindigenous men" was chosen as the reference category, owing to the focus of the study being on comparing loan access of indigenous women against nonindigenous women.

The null of no effects of ethnicity or gender on loan approval cannot be rejected at conventional significance levels in the estimated mixed-effects logistic regression. With a traditional frequentist approach, nonetheless, multicollinearity prevented the estimation of the interaction effects of ethnicity/gender on credit lending for indigenous women and indigenous men. To solve the problem of multicollinearity, a Bayesian approach was applied to estimate the mixed-effects logistic regression.

TABLE 5 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. the 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	Continuous		
Average sales of the client's business	Continuous		
Gender of the credit officer	Nominal	Characteristics of the credit officer	MCA
Years of experience in microfinance	Ordinal		
Years of experience as credit officer	Ordinal		
Education	Ordinal		
Marital status	Nominal		
Financial institution of the credit officer	Nominal		

TABLE 6 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					–
Nonindigenous women	1.71	0.08	37.29	0.34	0.732
Indigenous women[a]	–	–	–	–	–
Indigenous men[a]	–	–	–	–	–
	Estimate	**95% Confidence interval**			
Random-effects parameter	3.57	1.84	6.94		

[a]Multicollinearity prevented the estimation of the interaction effects of ethnicity/gender on credit lending for indigenous women and indigenous men

5.2 | Bayesian analysis

Table 7 and Figures 2 and 3 show the results of estimating the mixed-effects model with Bayesian methods. The results of the Bayesian estimation suggest that, with with a 95% probability, the combined effect of gender and ethnicity of a borrower is important for credit approval.

Point estimates of the odds ratio suggest that nonindigenous women have twice the chance of obtaining credit compared with nonindigenous men. In turn, indigenous women have 1.5 times the

TABLE 7 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					
Nonindigenous 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	0.77	1.73		

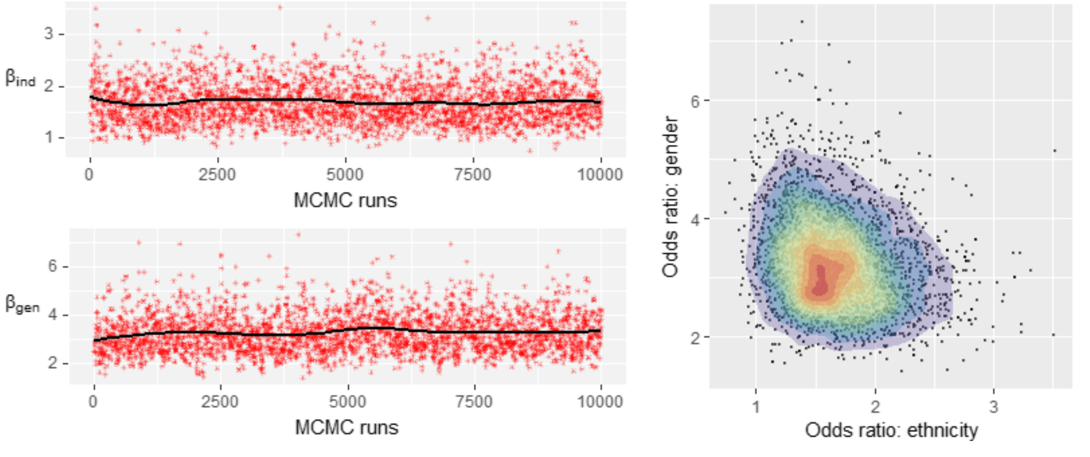

FIGURE 2 Bayesian estimation of treatment effects [Colour figure can be viewed at wileyonlinelibrary.com]

chance of obtaining credit compared with nonindigenous men. For indigenous and nonindigenous men, no differences were observed in their chances of obtaining credit (the 95% credible interval for the interaction effect of indigenous men was between 0.64 and 1.71, which includes 1, a value that indicates no discrimination effects)[5].

Figure 3 shows the interaction of the parameters of gender and ethnicity: even if both variables equally affect the chances of receiving a loan, the uppermost effect is caused by being a woman and this effect is reinforced in nonindigenous women.

Finally, in order to understand the nature of discrimination in the experiment (taste-based or statistical discrimination), two exercises with the participants were performed:

1. In the first exercise, participants were asked to sort the credit application files according to the order of review they would follow during the experiment. In this exercise, discrimination, if any, can be caused by taste-based discrimination (TBD) or statistical discrimination (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 review order of the applications; that is, as there was not enough information to make decisions about the applications, credit officers may have used the ethnicity/gender of the potential borrower as a proxy for the payment capacity of the applicant.

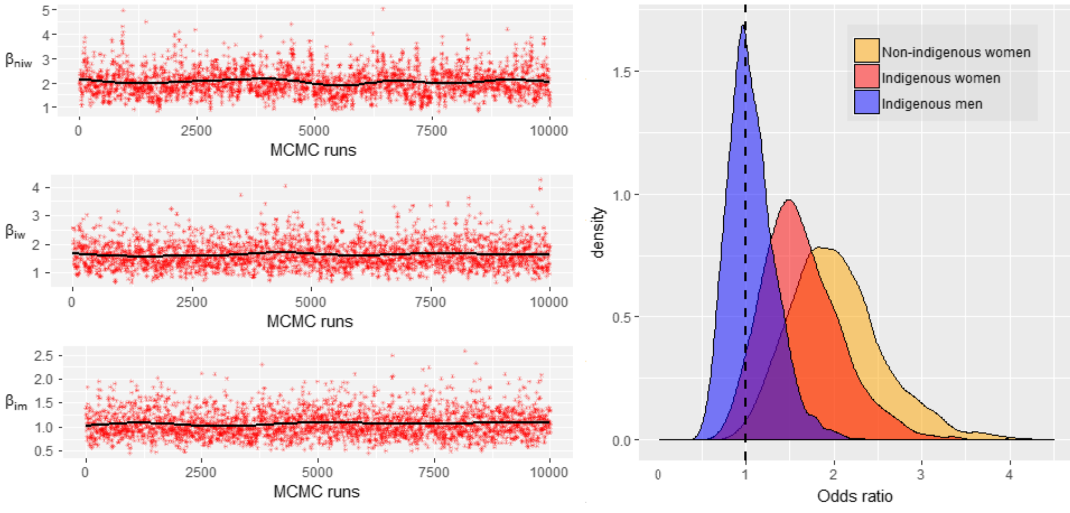

FIGURE 3 Bayesian estimation of interaction effects [Colour figure can be viewed at wileyonlinelibrary.com]

Table 8 shows the number of times that a specific credit application file was preferred for revision. A higher proportion of indigenous men's applications and nonindigenous women's applications (37% and 29%, respectively) were selected first for review, compared with indigenous women (21%) and nonindigenous men (13%).

1. In the second exercise, the participants were asked to sort the credit applications according to their preferences in loan disbursement for each client. This exercise was performed after all of the information was analyzed by the credit officers. 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 9 shows the preferences in loan disbursement for the second exercise. In this case there is a slight preference of disbursement for nonindigenous women (30%) and indigenous women (28%) over indigenous men (25%), and particularly over nonindigenous men (16%).

The statistical hypothesis of no differences in these proportions was evaluated by estimating the probability of preferences in loan disbursement by gender/ethnicity using a conjugate beta-binomial model (see Section A3 in the Appendix). Higher probabilities of preference in loan disbursement were observed for nonindigenous women—a result congruent with those of the mixed-effects logistic model—when compared with indigenous men (0.73) and to a lesser extent when compared with nonindigenous men and indigenous women (0.66). This last result could be interpreted as evidence of taste-based discrimination in credit lending favorable for nonindigenous women (Table 10).

6 | CONCLUSION

Evidence of preferences in loan allocation for nonindigenous women were found after estimating a Bayesian mixed-effects logistic model with data of a laboratory field experiment performed in Bolivia. The results that only take into account the effect of gender are limited and should be taken with care[6],

TABLE 8 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	

TABLE 9 Number of credit applications preferred for loan disbursement

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

TABLE 10 Probability of preferences in loan disbursement

Treatment	Preference	Probability
Nonindigenous female (Fni)	Fni ≻ Fi	0.66
	Fni ≻ Mi	0.73
	Fni ≻ Mni	0.66
Indigenous female (Fi)	Fi ≻ Fni	0.34
	Fi ≻ Mi	0.34
	Fi ≻ Mni	0.72
Nonindigenous male (Mni)	Mni ≻ Mi	0.34
	Mni ≻ Fi	0.28
	Mni ≻ Fni	0.34
Indigenous male (Mi)	Mi ≻ Mni	0.66
	Mi ≻ Fi	0.66
	Mi ≻ Fni	0.27

Note: Fni, Female, nonindigenous; Fi, Female, indigenous; Mi, Male, indigenous; Mni, Male, nonindigenous.

but more robust evidence was obtained for the combined effect of gender and ethnicity. The findings suggest that positive taste-based discrimination exists in credit lending for nonindigenous women compared with indigenous women in Bolivia.

From a theoretical point of view, the findings of the experiment are congruent with the general equilibrium model of credit market discrimination by Han (2004), where taste-based discrimination arose if loans to minority borrowers had lower expected rates of default loss; that is, if the participants of the experiment believed that the expected loan performance of nonindigenous women is better than that of indigenous women, a preference may have arisen. This could be the case in Bolivia, since Maclean (2010)—through an ethnographic study performed in this country—found that women use their social networks as a source of funding to repay their debts. This social collateral of nonindigenous women could be recognized by loan officers as an additional guarantee of loan repayment.

The results of discrimination in the study are also similar to those found by Agier and Szafarz (2013b), Labie et al. (2015), Jenq, Pan, and Theseira (2015), and Beisland, D'Espallier, and Mersland (2017). Agier and Szafarz (2013b) found that loan officer's subjectivity creates a gender gap in loan size in Brazil, while in turn Labie et al. (2015) found loan discrimination against disabled borrowers, performed by credit officers of a microfinance institution in Uganda. Jenq et al. (2015) analyzed peer-to-peer online microfinance and found that lenders tend to favor more attractive, lighter-skinned and less obese borrowers, a result that Jenq et al. (2015) do not attribute to statistical discrimination. Beisland et al. (2017) also find that credit officers with more experience provide smaller loans to young clients and clients with disabilities. Compared with the previous studies, our findings also support the evidence that credit officers in microfinance institutions tend to provide less credit to vulnerable groups of the population, in our case ethnic women[7].

Identity may have also played a role in the results if nonindigenous loan officers better appreciate the ability of nonethnic entrepreneurs in terms of completing their project and/or repaying the debt (Beck, Behr, & Madestam, 2011). It is evident in any case that the granting decision is based on the subjective judgment of loan officers drawing from previous experience (Baklouti & Baccar, 2013), and nonquantifiable data (Wilson, 2015), which creates room for discrimination and explains why different credit officers reached different conclusions after analyzing the same credit profile[8].

The practical and social implications of the findings are extremely relevant for 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 in 2012. Just as any other experiments, external validity—caused by the heterogeneity of the population in Bolivia—limits the generalization of the experimental results to other ethnic groups different from the Aymara nation. However, the results indicate that microfinance institutions and development organizations focused on providing loans to women have to take into account the interaction effect of ethnicity in order to properly develop interventions of financial inclusion that promote sustainable development[9].

In the practice, the interventions that seek to promote financial inclusion should be aimed at identifying both social desirability bias and the structural barriers to financial inclusion that indigenous women could face when accessing a loan. Social desirability bias makes credit officers hide their true preferences about ethnic minorities, and thus these officers may favor loan allocation in one specific ethnic group over another. Structural barriers in turn may affect credit allocation for indigenous women if the economic activity of indigenous female-owned businesses is less capital intensive or if indigenous females have lower financial literacy rates or experience language barriers.

Since women without access to credit are denied the chance of self-employment and economic opportunities relevant for empowerment and for breaking the cycle of intergenerational poverty (McDonnell, 2001), it is important to keep evaluating the existence of joint effects of gender and ethnicity in credit markets of countries with segregated ethnic groups.

Future studies can analyze the joint effects of gender and ethnicity in other financial services and in other stages of loan allocation process. Predatory lending, for example, implies that indigenous people and low-income borrowers are obtaining loans at high interest rates and with unfavorable terms. Also, in developing countries, geographical discrimination can arise if low-income indigenous communities are disproportionately located in areas or regions that lack equal access to financial services.

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ENDNOTES

[1] The Bolivian government issued a law against racism and all forms of discrimination promulgated by President Evo Morales as Law 737 on October 10, 2010. The New Financial Services Law of Bolivia was also introduced in August 2013. In terms of credit access, the New Financial Services Law sets limits on interest rates and the criteria of portfolio allocation for productive activities, and highlights in article 74 that the access of financial services must be on a basis of equal treatment, without discrimination by 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 had increased loan sizes and reduced the number of borrowers.

[2] Gangadhar and Malyadri (2015) add that women's economic empowerment through microfinance translates into better family decision-making, economic security, and legal awareness, and when combined with participation in seminars, workshops and training, they not only provide self-employment training but also facilitate good decision-making.

[3] Because of the ethnic diversity in Bolivia, La Paz and El Alto should not be considered representative of the Bolivian population, that is, the results are not generalizable at national level.

[4] The estimated intra-class correlation among the credit officers of the experiment was 0.7951, with a 95% confidence interval of 0.5073 to 0.9360. This value shows that the results of the evaluation of each folder are highly correlated for each credit officer.

[5] Good convergence and mixing of the MCMC chains were observed in the runs: the trajectory of the chains was stable over time in the trace plots (see Figures 3 and 4), the efficiency rates of the parameters were above 15%, and the Geweke's convergence diagnostic (Geweke, 1991) suggests that the chains were stationary (see Table 7).

[6] As was properly noted by one of the reviewers of this study, it is possible that the gender effect favorable for women found in the study is not entirely related to discrimination, since the credit profiles tend to be more favorable for women compared with men, for example, women (indigenous and nonindigenous) have more than twice as many assets as men. Women's profiles also have more than four times as much collateral as men. These imbalances are a consequence of the experiment being designed for balancing the folders of indigenous potential borrowers against nonindigenous potential borrowers. The unbalanced gender profiles is a limitation of the study, and while the experiment cannot be repeated, future research can seek to solve this limitation balancing both gender and ethnicity of potential borrowers.

[7] Labie et al. (2015) conclude that even in a nondiscriminatory welfare-maximizing financial institution a loan officer may discriminate, because eradicating discrimination would imply reducing loans, and thus observing a loan allocation biased against a minority group does not imply that the institution is biased against this group.

[8] Arya, Eckel, and Wichman (2013) showed that subjective aspects as trustworthiness are important for credit scores, owing to the difference between the ability to pay a debt and the willingness to pay, the latter being related to factors different from economic and financial capabilities. In terms of ethnic effects in trustworthiness, Karlan (2005) found differences in social capital and financial decisions between pairs of indigenous and nonindigenous groups, applying an experimental trust game in Ayacucho, a village of Peru. The results of the experiment are also similar to those of Asiedu, Freeman, and Nti-Addae (2012), who found that black-owned and Hispanic-owned firms faced more discrimination in obtaining credit, but, in contrast, white women-owned firms did not face discrimination in terms of access to loans, and in fact paid a lower interest rate than white male-owned firms. Agier (2012) nonetheless, proposes and estimates a structural model of the role of credit officers, but does not find any difference in outcomes between female and male credit officers, nor between clients of similar or different gender from their credit officer.

[9] From an organizational perspective, Mengoli, Odorici, and Gudjonsson (2017) found that, in microfinance institutions, females in operating roles are more effective in reducing gender discrimination than women in leading positions. Mengoli et al. (2017) conclude that gender equality in microfinance can be enhanced by gender equality advocates inside the organizations. In this line of thought, the findings of our study suggest that ethnic women in powerful positions at microfinance institutions can reduce discrimination in credit lending.

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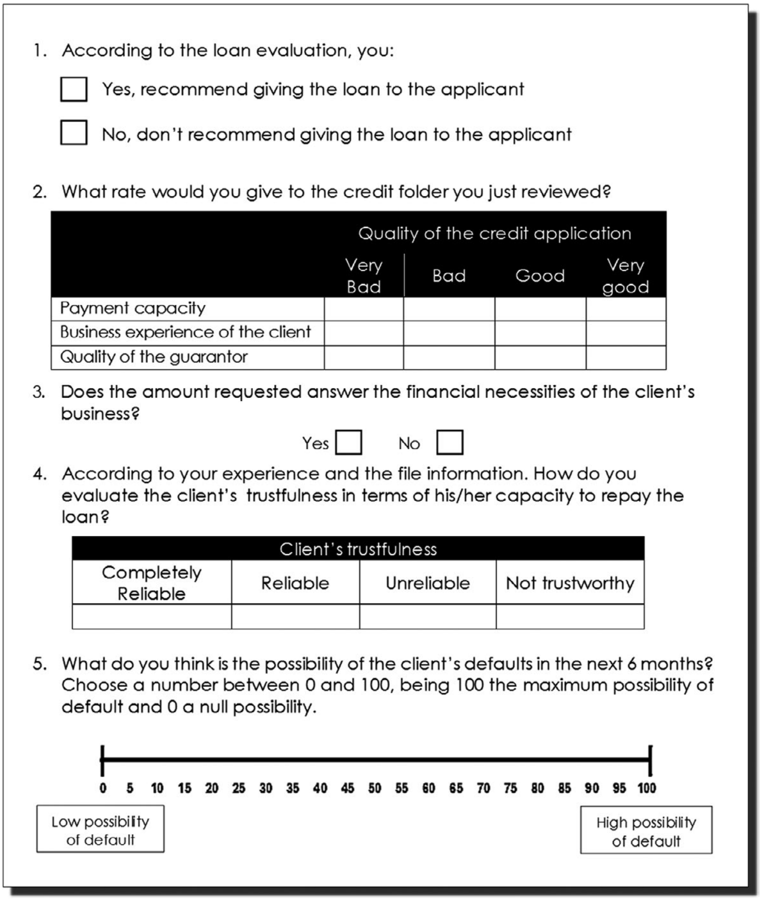
APPENDIX

A1 EVALUATION SHEET



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

FIGURE A1 Evaluation sheet provided to the participants

A2 ADDITIONAL ANALYSIS USED IN THE STUDY

This appendix shows the sensitivity of the empirical results to different values of prior hyper-parameters and to the inclusion of qualitative information in the form of interviews.

Let $\aleph \in \mathbb{R}$ be the reciprocal of the variance of a parameter. In the study, a value of $\aleph = 0.1$ around a zero mean was used for the precision hyper-parameters ν_{β_k}, τ_0, ν_0, ν_1 during the Bayesian estimation. Table A1 shows that when more variance (uncertainty) is allocated around the zero-mean betas (i.e., when $\aleph = 0.01$) the effect of gender lessens but women still have higher chances of loan approval compared with men. In contrast, when $\aleph = 1$ (when less uncertainty is placed in the zero-mean priors), women continue to have higher chances of loan approval compared with men, but the effect of gender increases and the gap of loan approval widens between indigenous and nonindigenous women. This last result suggests that stronger a priori beliefs about discrimination in the Bolivian credit markets can be used to unravel the evidence about ethnic/gender gaps in loan approval.

Qualitative research in the form of the consultation of experts was conducted to complement the results of the experiment. Interviews were held with the president of the Central Bank of Bolivia, the ex-Director of the Regulatory Authority of the Financial System in Bolivia, and the General Manager of CRECER, which is a development finance institution focused on providing microcredit and educational services to low-income women. All of the interviewed experts had more than 20 years of experience working in the microfinance sector of Bolivia. The interviews collected the perception of the respondents about (i) lending subjectivity, (ii) ethnic discrimination, and (iii) gender discrimination:

1. The three experts agreed that a degree of subjectivity exists when granting a loan because credit officers develop an intuition about the potential borrower, which plays a role when accepting or rejecting a loan, and also because sometimes there may be more empathy between the loan officer and the client, if the social group of the loan officer resembles that of the applicant.
2. For one of the respondents, being indigenous moderately restricts access to credit owing to language and idiosyncratic barriers, while for another respondent ethnic discrimination could act in reverse (i.e., in a favorable sense) as people in rural areas/indigenous people are considered more reliable becaue of the value of their word and honesty being much more important than in urban areas. The remaining respondent established that he had not seen significant differences of microcredit allocation in localities where the population was predominantly indigenous (Aymara or Quechua).
3. In relation to gender, the experts believe that there is a clear preference of microcredit lending for women because it is known that men and women handle their economic resources differently. Also, women are mostly linked to smaller activities with lower risk (such as trade, which makes the probability of women defaulting smaller) and men are more linked to productive activities, with higher credit risk. Also, for one of the experts, microfinance organizations are explicitly directed towards women because these institutions have the mission to support the initiatives of humble women from the popular sector in order to contribute to their empowerment and socioeconomic development.

The consultation of experts is not useful in discerning the existence of ethnic discrimination, owing to the conflicting opinions of experts about this subject. However, the qualitative evidence can be used to further evaluate the existence of preferences for women in the Bolivian credit market: following the opinion of the interviewed experts, a positive prior for gender equal to $\beta_{gen} = 1$ was allocated to the gender binary variable and a value of $\aleph = 0.01$ was used for the precision hyper-parameters ν_{β_k}, τ_0, ν_0, ν_1 (higher uncertainty

TABLE A1 Sensitivity analysis of the Bayesian estimation: Odds ratios of loan approval for different values of prior hyper-parameters

	Prior hyper-parameters			
	$\aleph$ = 0.1	**$\aleph$ = 0.01**	**$\aleph$ = 1**	**β_{gen} = 1 $\aleph$ = 0.01**
Ethnicity	1.63	1.18	1.75	1.13
Gender	3.17	1.39	5.10	3.25
Interaction effects				
Nonindigenous women	1.97	1.19	2.93	1.10
Indigenous women	1.58	1.17	1.83	1.09
Indigenous men	1.04	1.02	1.06	1.04
Synthetic covariates				
Evaluations of loan application	≈ 1	≈ 1	1.01	0.99
Credit profiles of the borrower	≈ 1	≈ 1	1.01	≈ 1
Credit officer's characteristics	≈ 1	≈ 1	≈ 1	≈ 1

was allocated to $\aleph$ because of the small number of experts consulted). The estimated results show that the odds ratio for gender effects is higher using these priors, as women are now 3.25 times more likely to receive a loan compared with men (see Table A1). This result indicates that if qualitative information based on the consultation with renowned experts is taken into account during the estimation of the Bayesian mixed-effects logistic model, the gender effect is more pronounced.

A3 METHODOLOGY USED IN THE STUDY

Ross and Yinger (2002) pointed out that the decision to approve or deny a loan is ideally suited for discrete choice empirical tools, such 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—see Train (2009). The Bayesian logit mixed-effects model of the study has the form:

$$\left\{\begin{array}{c} y_{i(h)} \left| \mathbf{x}_{i(h)} \sim (y_{i(h)} \left| \mathbf{x}_{i(h)} \right.\right.), \quad y \in \{0,1\}; \quad i = 1, \ldots, n_h \\ (y_{i(h)} \left| \mathbf{x}_{i(h)} \right.) = F * \left(\mathbf{x}^{\mathrm{T}}_{i(h)} \beta_{N_h}\right)^{y} \left[1 - F * \left(\mathbf{x}^{\mathrm{T}}_{i(h)} \beta_{N_h}\right)\right]^{y-1} \\ F * \left(\mathbf{x}^{\mathrm{T}} \beta\right) = P\left(Y = 1 \left| \mathbf{x}^{\mathrm{T}} \beta \right.\right) = \frac{\exp\left(\mathbf{x}^{\mathrm{T}} \beta\right)}{1 + \exp\left(\mathbf{x}^{\mathrm{T}} \beta\right)} \\ \mathbf{x}^{\mathrm{T}} \beta_{N_h} = \mathbf{x}^{\mathrm{T}} \beta + u_{0h} \\ \beta_k \sim N\left(0, \upsilon_{\beta_k}\right), \quad k = 1, \ldots, p \\ u_{0h} \left| \tau_0 \sim N\left(0, \tau_0\right), \quad h = 1, \ldots, N_h \right. \\ \tau_0 \sim IG\left(\nu_0, \nu 1\right) \end{array}\right. \tag{1}$$

In the 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, Wang, Yvonnet, and Coursaget (1993), Holmes and Held (2006), Karabatsos (2015), and 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 hyper-parameters $v_{\beta_k} = \tau_0 = \nu_0 = \nu_1 = 0.1$ 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 nonindigenous 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 Glennerster and Takavarasha (2013) to reduce unexplained variance; as the control variables were highly correlated, they were summarized into synthetic covariates in order 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 covariates were 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. See Husson, Lê, & Pàges (2010) for details regarding these techniques.

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 32,498 iterations, a thin parameter equal to 3, and a burn-in of 2,500 samples. Point estimates of β_k were obtained minimizing the expected loss of a squared-error function; that is, the Bayesian point estimators are the mean of the posterior distribution of β_k (see Gill, 2014). Odds ratios calculated with e^{β_k}—where e is the Napier's (Euler's) constant—were used to measure the association between the exposure and the outcome of the experiment, as a result of its convenient interpretation: if $e^{\beta_k} = 1$, there will be no relationship between loan approval and the ethnicity/gender of the potential borrower, but if $e^{\beta_k} > 1$ ($e^{\beta_k} < 1$) the exposure will be associated with higher (lower) odds of loan approval (see Bland, 2000; Szumilas, 2010).

The logistic mixed-effects model was estimated with classical (frequentist) methods or with Bayesian methods, see Regier, Ryan, Phimister, and Marra (2009). Under the frequentist paradigm, the null of no effects of ethnicity on loan allocation was evaluated with conventional procedures such as p values. In contrast, the Bayesian approach in experimental economics—suggested by inter alia El-Gamal and Palfrey (1996) or Bolton, Fong, and Mosquin (2003) and used by authors such as Cipriani, Costantini, and Guarino (2012)—allows one to measure the strength of evidence in favor or against a hypothesis; in this case, the extent to which the data increase or decrease the odds of discrimination during a loan evaluation.

An additional reason to use a Bayesian approach was that the sample size of 280 credit files evaluated by 70 credit officers—a number stemmed from the research protocol and the available resources to implement the experiment—may cause an inaccurate maximum likelihood (ML) estimation of the multilevel effects. Bayesian methods in contrast do not assume asymptotics (large samples), as is the case with ML estimation, and thus, can be used to properly estimate the mixed-effects model with small data sets while retaining precision and without losing power (Van de Schoot, Broere, Perryck, Zondervan-Zwijnenburg, & Van Loey, 2015). McNeish (2016) further showed that researchers do not need to have extensive prior information to obtain useful Bayesian MCMC estimates in small samples, if the prior is set in the vague vicinity of the population value, even with a fairly large variance. In a study of the analysis of a small sample of multilevel data with a complex variance structure, Baldwin and Fellingham (2013) also favor the Bayesian estimator with carefully chosen prior hyper-parameters over adjusted restricted maximum likelihood, as the Bayesian approach does the best job balancing bias and efficiency.

The statistical hypothesis of no differences in the proportions of loan allocation between gender and ethnic groups was evaluated through the estimating of the probability of preferences in loan disbursement, using a conjugate beta-binomial model. Let f_1 be an observed frequency with a marginal that will be compared with another frequency f_2 with n_2 from Table 7, if,

$$f_1 \sim \text{Binom}(n_1, \theta_1), \text{ and} \tag{2}$$

$$f_2 \sim \text{Binom}(n_2, \theta_2), \tag{3}$$

with the proportions $\theta_1 \in [0,1]$, $\theta_2 \in [0,1]$ that follow a beta distribution $\theta_1 \sim B(1\text{E}10^2, 1\text{E}10^2)$, $\theta_2 \sim B(1\text{E}10^2, 1\text{E}10^2)$ centered on an equi-probability of 0.5 (i.e., the Laplace principle of indifference), then,

$$p(\theta_1|f_1,n_1) \sim B(\theta_1|y_1 + 1\text{E}10^2, n_1 - y_1 + 1\text{E}10^2), \tag{4}$$

$$p(\theta_2|f_2,n_2) \sim B(\theta_2|y_2 + 1\text{E}10^2, n_2 - y_2 + 1\text{E}10^2), \tag{5}$$

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

$$p(\delta|f,n) = \int_0^\infty B(\theta\,|y_1 + 1\text{E}10^2, n_1 - y_1 + 1\text{E}10^2)B(\theta - \delta|y_2 + 1\text{E}10^2, n_2 - y_2 + 1\text{E}10^2)d\theta \tag{6}$$

analytically or with a Monte Carlo approximation.