BOLIVIAN ECONOMIC RESEARCH PAPERS, 2017, Vol 2(1)

MICROCREDIT WAS EFFECTIVE IN REDUCING POVERTY AND EMPOWERING WOMEN AT SUBNATIONAL LEVEL IN BOLIVIA: EVIDENCE FROM A QUASI-EXPERIMENTAL BAYESIAN SPATIAL MODEL

Rolando Gonzales Martínez and Patricia Aranda Blanco*

ABSTRACT

Gonzales et al. (2017) developed a quasi-experimental Bayesian spatial model to assess the social impact of microcredit at municipal level in Bolivia and found that microfinance had a positive impact on poverty reduction and empowerment of women in this country. Furthermore, the paper discusses the findings within the context of the guidelines of Bolivia's Financial Services Law and Patriotic Agenda 2025.

Classification JEL: C11, C31, G21.
Keywords: Bayesian Methods, Microcredit, Spatial Statistics, Matching.

* Researchers of the Bayesian Institute for Research on Development. The content of this paper is the sole responsibility of the authors and does not represent the opinion of the Ministry of Economy and Public Finance. Any comments can be emailed to rgonzales@bayesgroup.org or paranda2008@hotmail.com.

I. INTRODUCTION

The microfinance sector provides low-income customers with no access to traditional banking services with small-scale financial services (Karlan and Goldberg, 2007). The impact of microfinance is a controversial topic: the advocates of this model —among whom Nobel Prize winner Muhammand Yunus or World Bank President Jim Yong Kim— assert that microfinance reduces poverty through the generation of employment and more income, which in turn improves the state of health and education of the population. The critics of microfinance, on the other hand, do not believe that microfinance has an impact on poverty reduction and rather suggest that it is an obstacle for regional development since it leads to crowding-out of the productive and formal activities; see for example Bateman (2010).

Assessments of the impact of microfinance tend to be qualitative and based on anecdotal evidence —see Weiss and Montgomery (2005)— or to focus on individual cases or households, as in Banerjee (2015). In order to overcome both constraints, Gonzales et.al. (2017) developed a quasi-experimental impact assessment spatial algorithm, which they use to solve the problem of making an appropriate estimation of the impact of microcredit at the regional level. This quasi-experimental impact assessment is justified in the sense that it is highly relevant to understand whether microcredit has had a favorable or unfavorable impact at the municipal level in Bolivia, with the aim of properly channeling the regional policies of financial inclusion of this country. This article describes the algorithm of Gonzales et.al. *op.cit.* and discusses the results within the framework of the guidelines of new Financial Services Law N°393 and Bolivian economic and social development plan (Patriotic Agenda 2025).

Section 2 contains a brief literature review about the regional impact of microfinance. Section 3 describes the quasi-experimental impact assessment algorithm. Section 4 presents application for the Bolivian case. Section 5 discusses the results. Annex 1 shows a falsification test to make an evaluation of the advantages and limitations of the BS-PSM algorithm. Annex 2 makes an analysis of robustness of the results in case of changes in the matching techniques and when excluding spatial effects. The MatLab code used in the study is available on request.

II. REGIONAL IMPACT OF MICROFINANCE

Microcredit has a regional impact when it affects both the customers accessing this financial service and other economic agents in the same geographic region or other nearby regions, as a result of the economic interaction between the borrowers and the rest of the population without access to credits. These regional effects are measured with spatial models like the ones described in Anselin (1988), Arbia (2010), Anselin and Florax (2011), or Griffith and Paelinck (2011). These models seek to capture the effects of financing services in a local economy and in neighboring regions as a result of the commercial and market relationships among regions and the mobility of the production factors (Capello, 2009).

The favorable impact of microfinance on poverty at the regional level may be presented in the form of the economic boost resulting from the borrowers' investment in the region or in nearby regions (Glennerster and Takavarasha, 2013). On the other hand, negative effects may occur if the microfinancial entities grant loans to short-lived informal and unproductive companies (Bateman, 2013), which may give rise to a crowding-out effect in the region if benefiting informal employment and self-employment deters the operation of formal small and medium-sized companies with prospects for technological improvement, widely recognized as a source of formal employment and growth in developing countries —see Bateman and Chang (2009), Bateman (2010) or Bateman (2013).

With regard to the impact of microfinance on the empowerment of women, Glennerster and Tavarasha (2013) provide an excellent example of this phenomenon: there may be positive effects when, within a region or community, women start with an economic activity with the credits received and employ their neighbors, generating employment and ensuring distribution of the income obtained. Thus, the benefit of the loan even reaches women who did not have access to the credit because of the mere fact that they live in the region where microcredit is available. Negative effects occur if women with existing businesses suffer from growing competition when new borrowers set up business in the same community and offer similar products.

Some empirical studies on the impact of microfinance are, *inter alia*, Mosley (2003), Mosley and Rock (2004), Khalily (2004), Wright and Copestake (2004), Chowdhury and Bhuiya (2004), Johnson (2004), Velasco and Marconi (2004), or McIntosh (2008). In terms of positive effects, these studies found that microfinance stabilizes income at the regional level (Mosley, 2003), generates a demand that boosts the economy through the labor market (Mosley and Roca, 2004) and helps the micro enterprises maintain a growing level of production and investment, even when there is a slowdown (Velasco and Marconi, 2004). In terms of negative effects, Velasco and Marconi (2004) found that the credits are sometimes used for consumption rather than production, giving rise to a problem in the debtor's payment discipline.

In the case of Bolivia, some of the studies analyzing the impact of microfinance are MkNelly and Dunford (1999), Navajas, Schreiner, Meyer, Gonzales-Vega and Rodriguez-Meza (2000), Mosley (2001), Brett (2006), Velasco and Marconi (2004), and Gonzales (2010). MkNelly and Dunford (1999) assess the social impact of microcredit by comparing nutritional data two years after the communities were offered loans. The authors did not find evidence of an improved food security among the households or an improved nutritional status of the credit customers' children, compared to the control group. Navajas et al. (2000) compared the level of poverty among the borrowers to that of other households in La Paz and found that microfinance does not normally target the poorest people but rather people near the poverty line. Using data on Bolivian microborrowers and a control sample with a before-after methodology, Mosley (2001) found that growth of the income and assets of the borrowers is always greater compared to the control group, but there is no evidence of this effect among people living in extreme poverty. More recently, in his suggestive ethnographic article entitled "We Sacrifice and Eat Less: The Structural Complexities of Microfinance Participation", Brett (2006) found that, after accessing microcredit to set up a small business, many women in El Alto are unable to generate sufficient income to pay their debt and therefore have to use money for household expenses, which means that they sometimes have less money for food. Finally, Gonzales (2010) analyzed the regional impact of credit in developing economies and found that, on average, the municipalities with access to financial services have better human development indicators.

Albeit that Velasco and Marconi (2004) or Gonzales (2010) previously analyzed the regional impact of microfinance in Bolivia, with the new information from the 2012 National Population and Housing Census, showing that it is possible to make a more complete analysis of the regional impact of having access to microcredit in all Bolivian municipalities. In addition, previous studies did not make a rigorous impact assessment, which is why a quasi-experimental spatial design is a methodological improvement compared to previous studies.

III. BAYESIAN SPATIAL-PROPENSITY SCORE MATCHING (BS-PSM)

This section describes the BS-PSM quasi-experimental algorithm used to assess regional impacts. Where t is a binary vector of values $n \times 1$, which reflect the presence, or absence, of treatment (in this case microfinance) in a region $i = 1, 2, \ldots, n$ (in this case, the $i = 1, 2, \ldots, 339$ municipalities of Bolivia). The spatial dependence among the regions is estimated with a Spatial Error Model (SEM) that captures the influence of spillover effects through an error term ε,

$$\begin{cases} t = X\beta + \varepsilon \\ \varepsilon = \rho W \varepsilon + \upsilon, \quad \upsilon \sim \mathcal{N}\left(0,\ \sigma_{\upsilon}^{2} I_n\right) \end{cases} \tag{1}$$

where ρ is the spatial correlation coefficient, W is a stochastic square matrix of $n \times n$ regions, and X is a matrix $n \times p$ with p-control covariants for the n regions,

$$X = \begin{pmatrix} x_{11} & \cdots & x_{1p} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{np} \end{pmatrix} \tag{2}$$

which captures the autocorrelated spatial shocks in the error term (Elhorst, 2014). The Bayesian approach for modeling this type of spatial and limited dependent variables treats binary observations 0,1 in t as indicators of the unobserved latent net utility of a spatial agent in region i. Formally, based on the difference among utilities $u_{1i} - u_{0i}$, $i = 1, \ldots, n,$ associated to observed $0,1$ choice indicators, the probit model assumes that the difference $t_i^* = u_{1i} - u_{0i}$ follows a Gauss-Laplace distribution, and, since t_i^* is not observable, $t_i = 1$ if $t_i^* \geq 0$ and $t = 0$ if $t_i^* < 0$. This implies that $\mathbb{P}(t_i = 1) = \mathbb{P}(u_{1i} \geq u_{0i}) = \mathbb{P}\left(t_i^* \geq 0\right)$. Therefore, a likelihood function for an SEM model is,

$$\mathcal{L}\left(t, W \mid \beta, \rho, \sigma_{\upsilon}^{2}\right) = \frac{1}{2\pi\sigma_{\upsilon}^{2n/2}} \left| I_n - \rho W \right| \exp\left\{ -\frac{1}{2\sigma_{\upsilon}^{2}} \varepsilon' \varepsilon \right\} \tag{3}$$

with $\varepsilon = \left(I_n - \rho W\right)\left(t - X\beta\right)$. Using a diffuse prior for $\beta,\ \rho,\ \sigma_{\upsilon}^{2}$, the joint conditional function for these parameters becomes,

$$\mathbb{P}\left(\beta,\rho,\sigma_{\upsilon}^{2} \mid t,W\right) \propto \left|I_{n}-\rho W\right| \sigma_{\upsilon}^{-(n+1)} \exp\left\{-\frac{1}{2\sigma_{\upsilon}^{2}}\varepsilon'\varepsilon\right\} \tag{4}$$

with a nucleus:

$$\mathbb{P}\left(\sigma_{\upsilon}^{2} \mid \beta,\rho\right) \propto \sigma_{\upsilon}^{-(n+1)} \exp\left\{-\frac{1}{2\sigma_{\upsilon}^{2}}\varepsilon'\varepsilon\right\} \tag{5}$$

for the conditional posterior function of σ_{υ}^{2}, and:

$$\mathbb{P}\left(\beta \mid \rho,\sigma_{\upsilon}^{2}\right) \sim \mathcal{N}\left(\beta,\sigma_{\upsilon}^{2}\left(X'\mathrm{B'BX}\right)^{-1}\right) \tag{6}$$

$$\beta=\left(\mathrm{X'B'BX}\right)^{-1}\left(X'B'Bt\right) \tag{7}$$

$$B=\left(I_{n}-\rho W\right) \tag{8}$$

for the multivariate Gaussian conditional distribution of β. The conditional distribution of ρ given β and σ_{υ}^{2} is:

$$\mathbb{P}\left(\rho \mid \beta,\sigma_{\upsilon}^{2}\right) \propto \left|I_{n}-\rho W\right| \sigma_{\upsilon}^{-(n+1)} \exp\left\{-\frac{1}{2\sigma_{\upsilon}^{2}}\varepsilon'\varepsilon\right\} \tag{9}$$

LeSage (2000) proposed a Monte Carlo Markov Chain (MCMC) estimator to generate samples of this last distribution. Also see LeSage and Pace (2009).

Based on the probabilities calculated with the SEM model, it is possible to use matching estimators to compare a region that received treatment (in this case a municipality with access to microcredit) with members of a comparison group (municipalities without access to microcredit but with similar characteristics as the municipality with access). Be $\hat{p}:=\mathbb{P}\left(t_{i}=1\right)=f\left(\hat{\rho}W\varepsilon,X\beta\right)$ the estimated probabilities of the spatial probit model. A traditional matching estimator of close neighbors between treated and untreated regions is:

$$C_{nn}\left(\hat{p}\right)=\min_{j} \| \hat{p}_{i}-\hat{p}_{j} \|, \text{ with } j \in n_{0} \tag{10}$$

where n_{0} is the group of untreated regions (i.e. the municipalities without access to financial services). In this type of matching, the score of a treated i-region is compared to the scores of all untreated j-regions, with the objective of finding an untreated region with a score similar to that of the treated region. However, this strategy may lead to an erroneous matching if the nearest neighbor is very far from the treated region (Caliendo and Kopeinig, 2008). This problem can be avoided by imposing a level of tolerance on the maximum distance between scores, i.e. a caliper: be δ a measure of proximity between the centroids of the regional polygons, calculated on the basis of matrix of distances W, if δ is taken into account during the matching, then:

$$C_{sc}\left(\hat{p}, W\right) = \min_{j} \hat{p}_i - \delta_j \hat{p}_j, \text{ with } j \in n_0 \tag{11}$$

the score $\hat{p}_i$ of a treated i-region will be compared only to the scores of untreated adjacent or nearby regions. This is a type of Spatial Caliper Matching (SCM), in which the tolerance is given by the geographic nearness between the regions. The Spatial Average Treatment Effect (SATE) estimated with this method is:

$$\text{SATE} = \vartheta_u = \mathcal{M}\left(t, W, X, y, \Theta\right) \tag{12}$$

$$= \mathbb{E}_{W,\Theta}\left\{\left(y_i \mid t_i = 1, X_{1i} = x_1, \ldots, X_{pi} = x_p\right) - \left(y_i \mid t_i = 0, X_{1i} = x_1, \ldots, X_{pi} = x_p\right)\right\}$$

where y represents a regional impact variable, $\mathcal{M}(\cdot)$ is a matching function and $\left\{\beta, \rho, \sigma_\upsilon^2\right\} \in \Theta$ is a stacked vector of parameters of the spatial discrete choice model. An estimation of the SATE can be calculated with $\left\{\hat{p}^{(1)}, \hat{p}^{(2)}, \ldots., \hat{p}^{(g)}\right\}$ using a g-sample of $\mathbb{P}\left(\beta^{(g)} \mid \rho, \sigma_\upsilon^2\right)$ and $\mathbb{P}\left(\rho^{(g)} \mid \beta, \sigma_\upsilon^2\right)$ of the spatial probit model; therefore:

$$C_{sc}\left(\hat{p}^{(g)}, W\right) = \min_{j} \| \hat{p}_i^{(g)} - \delta_j \hat{p}_j^{(g)} \| \tag{13}$$

and the complete density of the SATE can be obtained with the $g = 1, \ldots, G$-runs of the MCMC sampler:

$$\left\{\mathcal{M}\left(t, W, X, y, \Theta^{(g)}\right)\right\}_{g=1}^{G} \tag{14}$$

See, *inter alia*, Chib and Greenberg (2010), or Alvarez and Levin (2014). Using this density, it is possible to calculate point statistics and credibility intervals: be ϑ a SATE, a Bayesian point estimation $\hat{\vartheta}$ will be the value of ϑ that minimizes the expected value of a loss function $\ell\left(\hat{\vartheta}, \vartheta\right)$, taking the expectation of the posterior distribution function of ϑ, $\pi\left(\vartheta \mid \mathcal{D}\right)$:

$$\min_{\hat{\vartheta}} \mathbb{E}\left[\ell\left(\hat{\vartheta}, \vartheta\right)\right] = \min_{\hat{\vartheta}} \int \ell\left(\hat{\vartheta}, \vartheta\right) \pi\left(\vartheta \mid \mathcal{D}\right) d\vartheta \tag{15}$$

Under quadratic loss,

$$\min_{\hat{\vartheta}} \mathbb{E}\left[\ell\left(\hat{\vartheta},\vartheta\right)\right]=\min_{\hat{\vartheta}}\int\left(\hat{\vartheta}-\vartheta\right)^2\pi\left(\vartheta\,|\,\mathcal{D}\right)d\vartheta \tag{16}$$

See Geweke (2005) or Gill (2007). An $\gamma=1-\alpha$ Bayesian credibility interval $\mathbb{C}_{\vartheta,\gamma}$ for the SATE will be a subregion of the probability space parameterized by $\vartheta\in\Theta$; see *-inter alia-* Shalloway (2014).

Since propensity score matching is a two-stage estimation technique, the standard error of the mean treatment effect has to be adjusted to take into account the uncertainty in the first stage of estimation of the score (Gelman and Hill, 2007). Compared to variance adjustment methods, the use of Bayesian methods ensures that positive standard errors are obtained. Additionally, in case of small data samples, maximum likelihood suffers from low power and produces biased estimators. This problem can be overcome by using a Bayesian estimation with informative priors; see Van de Schoot, Broere, Perryck, Zondervan-Zwijnenburg and Van Loey (2015). In order to evaluate the advantages and limitations of the BS-PSM algorithm, Annex 1 at the end of the study shows a falsification test that evaluates the impact of microcredit on deafness of the inhabitants of a municipality. Annex 2 contains an additional analysis of robustness of the BS-PSM algorithm in case of changes in the matching technique and excluding spatial effects.

IV. REGIONAL EFFECTS OF MICROFINANCE IN BOLIVIA

Bolivia is an interesting case study to make an assessment of the regional effects of microcredit in view of its paradigmatic microfinance history. The first microcredit initiatives in Bolivia were led by Non-Governmental Organizations (NGOs) in the 1980s. In the 1990s, several NGOs became regulated microfinance institutions. The rapid growth and the high earnings of these institutions attracted investors to the market and Bolivia became one of the best environments for microfinance development in the world. Together with Peru, the country was ranked among the top in the Global Microscope prepared by the Inter-American Development Bank (IDB). In order to evaluate the regional impact of this development, the BS-PSM was used in the field of microfinance in Bolivia, comparing the differences between the Bolivian municipalities with and without access to this financial service, thus testing the effects of microcredit –as the main microfinance product— on poverty, female empowerment and informality in Bolivia. The probability of access to financing was estimated on the basis of the spatial distances between municipalities in matrix W, and the control covariates in each municipality, contained in X.

Data and variables. The information of the National Population and Housing Census 2012 was used to calculate demographic variables at the municipal level in Bolivia. The information about microcredit was obtained from the Authority for Supervision of the Financial System and the data to estimate informality were obtained from the Bolivia Household Survey 2012.

The regional access to microfinance was measured based on the number of microcredit operations in Bolivian municipalities. Be $\mathbb{N}_i$ the number of microcredit operations with $i=1,\ldots,n$, divided by the economically active population of every municipality. Binary treatment variable t_i in financial access vector $\mathbf{t}$ is equal to:

$$t_i = \begin{cases} 1 \;\; si \;\; \mathbb{N}_i \geq Q \\ 0 \;\; si \;\; \mathbb{N}_i < Q \end{cases} \tag{17}$$

where $Q \in \mathbb{R}^+$ are percentiles of the number of microcredit operations in every region. Using this quasi-continuous estimation, it is possible to measure the differential impact of the number of microcredit operations on poverty, the empowerment of women and informality. This approach is similar to the different dose response function proposed by Hirano and Imbens (2004).

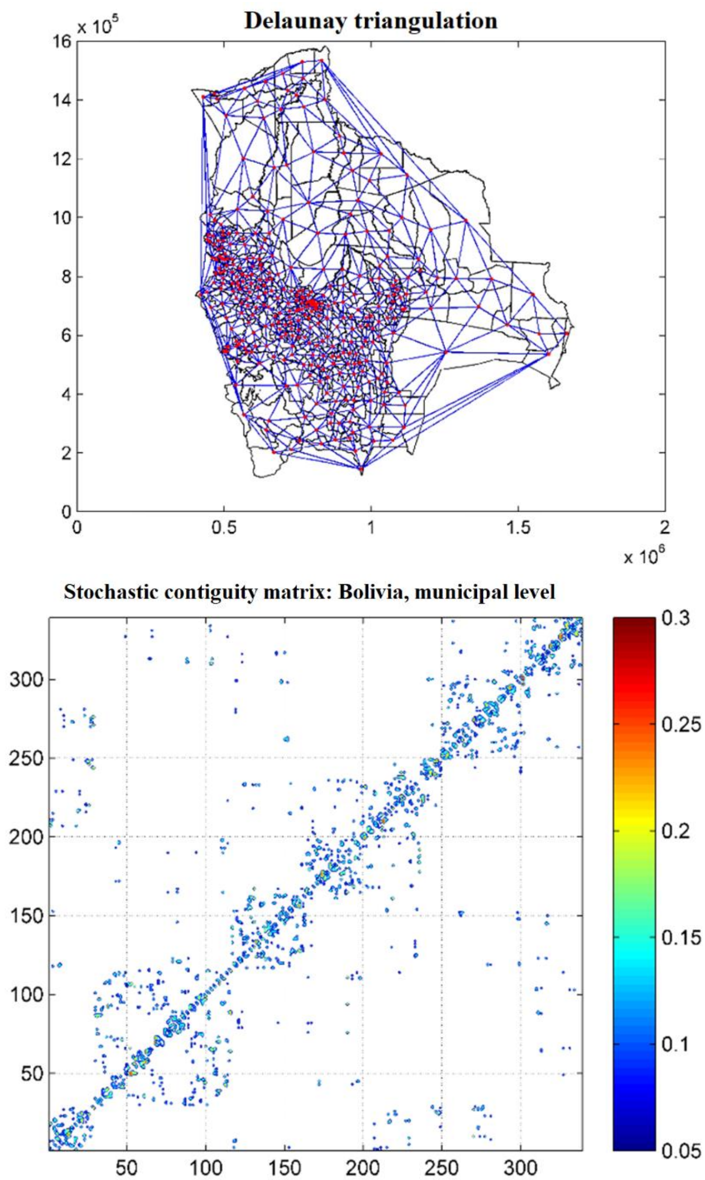
Matrix X of control covariates 339×9 is made up of 9 variables for each of the 339 Bolivian municipalities:

(1) Total population.
(2) Potential offer of employment, measured as the percentage of the working-age population older than 15 years of age over the total population (this indicator seeks to capture the percentage of individuals offering or old enough to offer their work in the labor market).
(3) Precarious waste disposal, a proxy variable of the standard of living, measured as the percentage of households in a municipality that do not use the garbage collection service (through the garbage truck) and rather dispose of their garbage in public spaces or on the riverbank.
(4) Place where the woman gave birth, which is not a health center, as a proxy variable of the standard of living in a municipality.
(5) Percentage of the population living in the rural area.
(6) Percentage of the population with access to electricity.
(7) Percentage of children in the population.
(8) Overall rate of participation of women, as an indicator of employment that shows the size of the female labor force.
(9) Schools per capita, measured as the number of schools divided by the number of inhabitants of the municipality.

Variables (1) to (8) were calculated on the basis of information of the National Population and Housing Census 2012; variable (9) was obtained from administrative records. These variables were selected from among a broader set of variables (A General Unrestricted Model or GUM) which was reduced to the final specification, using a general-to-specific methodology (Campos et al., 2005). The original GUM —i.e. the more general statistical model initially postulated, given the available data, prior empirical and theoretical evidence, and any available additional information (Hendry and Nielsen, 2007)— originally included a large number of variables prepared with census information, e.g. the average number of schooling of the population, migration, the number of households that have a vehicle or the number of self-employed persons in the municipality, among other variables.

In terms of impact variables, poverty was measured on the basis of the method of Unsatisfied Basic Needs (UBN) as a multidimensional measure of poverty that takes into account variables such as the quality of the house, the access to potable water, the access to basic sanitation, education, electricity and the consumption capacity of the households; see ECLAC (2009). The empowerment of women was calculated on the basis of the percentage of women household heads in a municipality, excluding the ones who are household heads because they are divorced, separated or widowed. This variable measures empowerment based on decision-making at the household level, since the woman is the household head even when she has a husband or partner; Yogerdrarajah (2013) used a similar measure of empowerment. The measurement of informality was based on the proxy variable of the household not being registered in the pension system in the Bolivia Household Survey 2012. This approximation of informality was also used by the World Bank (2009) to analyze the reasons and the impact of informality in Bolivia.

Graph 1: Delaunay triangulation and *W* approximation matrix

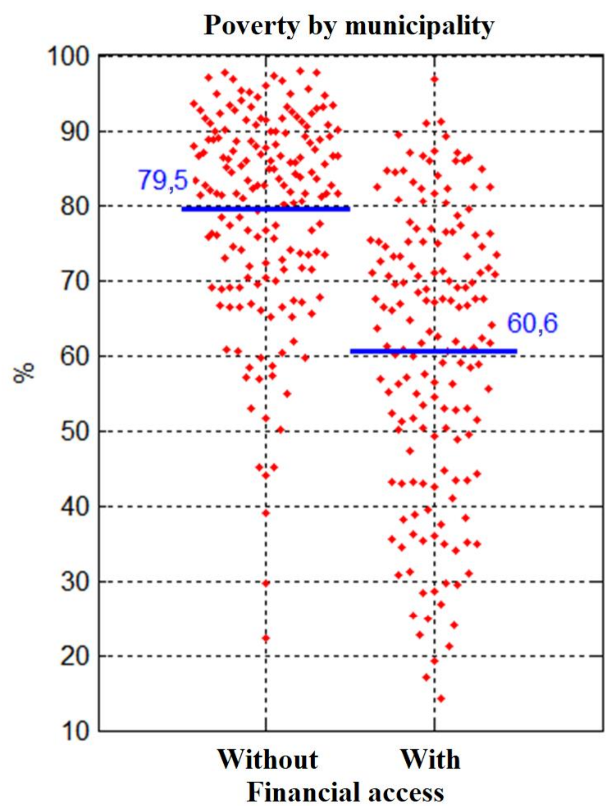


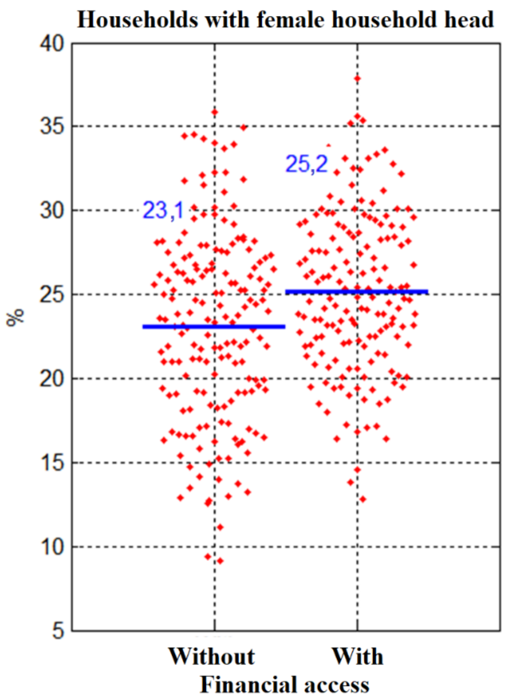
Matrix of municipal contiguity. Based on Bolivia's Geographic Information System (GIS) for 2012, a *W* approximation matrix of 339×339 was built, calculating the Euclidian distance between the centroids of the 339 Bolivian municipalities, satisfying the Delaunay triangulation condition (Graph 1).

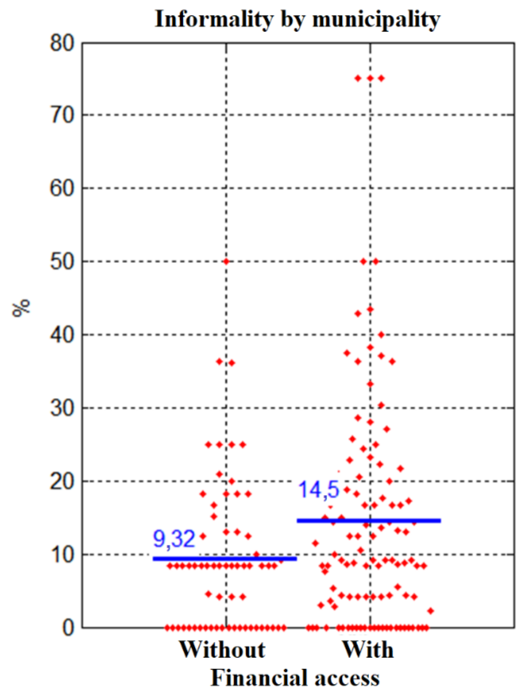
Differences observed at municipal level. Graph 2 shows differences in terms of poverty and empowerment in the 339 municipalities of Bolivia, comparing the municipalities with access to financial services to the ones without access to financial services (each point in the graph is a municipality). In the case of informality, there are household survey data for only 173 municipalities.

On average, the UBN indicator shows that 79.5% of the population lived in poverty conditions based in UBN measurements in the municipalities without financial access, while the percentage of UBN-based poverty in the municipalities with access to financial services was approximately 18 percentage points (pp) lower, at an average 61% in 2012. In terms of the empowerment of women, the percentage of women recognized as household heads in the municipalities with access to financial services averaged 25.2%, i.e. 2.1 pp higher than the average in municipalities with no access to financial services. With regard to informality, in 2012 the municipalities with access had a higher percentage of informality (14.5%), of 5.2 pp more than the municipalities without financial access (9.32%).

Graph 2: Differences observed at municipal level







Nonetheless, these differences in terms of poverty, empowerment of women and informality between the municipalities with access and without access to financial services **cannot** be attributed entirely to microcredit since there are other idiosyncratic (demographic, social and economic) factors in each municipality which may explain the differences in the indicators on poverty, empowerment of women and informality. The objective of quasi-experimental methods like BS-PSM is precisely to try to isolate the effect of interest from other idiosyncratic effects, through the comparison of municipalities with financial access to municipalities without financial access, which are similar to the municipalities with access whereby both groups are similar in demographic, social and economic terms.

Spatial effects of microfinance in Bolivia. Graphs 3, 4, 5 and tables 1 and 2 show the results of estimating the impact of microcredit at municipal level in Bolivia, calculated with BS-PSM. Graphs 3, 4 and 5 show the probability distributions of the differences of the variables analyzed for each percentile of treatment, together with the Monte Carlo Markov Chain (MCMC) used to approximate these distributions. During the estimation of the BS-PSM model, a prior of $\pi(\rho) \sim U(0,1)$ was used for spatial correlation coefficient ρ, reflecting the fact that the presence of an entity providing financial services in a municipality increases the possibilities of the population in nearby municipalities accessing financial services, i.e. a positive spatial correlation in financial access. For the impact in each percentile Q of microcredit operations, chains of 1100 iterations were simulated and a burn-in of 100 iterations was chosen to discard the non-stationary part of the chain (i.e., 110 thousand iterations of the MCMC sample were run and 10 thousand were discarded). An autocorrelation was found in the simulated chains. In order to eliminate this correlation, the method of thinning the iterations was applied, but since the results obtained with the chains with and without thinning were not extremely different, the estimators of the SATE are based on the unthinned chains; see Link and Eaton (2012) for a discussion on the use of thinning. Statistics and post-estimation tests were calculated to evaluate the spatial models, using statistic pseudo-R^2 proposed by Efron (1978) and the Bayesian version of the balance test proposed by Gonzales (2015).

The most conclusive evidence of the regional impacts was obtained for poverty and the empowerment of women. The evidence concerning informality is weak and inconclusive:

1) Poverty. Strong evidence was found of the impact of microcredit on the reduction of poverty at the municipal level. The credibility interval at 95% does not include zero at any of the Q centiles of microfinance operations (Graph 3, left) and the MCMC chains are strongly stationary for each centile (Graph 3, right). Table 1 shows that, on average the municipalities with access to micro credit tend to have around 11 pp less population living in UBN-based poverty, compared to the municipalities without access to microfinance. This difference of 11 pp in poverty is lower than the difference of 18 pp in case of a simple comparison of the municipalities with and without access to financial services, which shows that after controlling for the socioeconomic, demographic and spatial characteristics of every municipality, the impact of microcredit on poverty reduction is small, but favorable all the same.

2) Empowerment of women. With a credibility interval of 95%, the impact of microcredit on the empowerment of women was estimated to be above zero for the different intensities of microcredit provision captured in each percentile Q, showing that the percentage of women who are household heads is higher in the municipalities with access to microcredit, even after controlling for the spatial distance and the population characteristics of the municipalities. The MCMC chains are once again stationary in each percentile Q (Graph 4, right) and there is a good convergence thereof. Remarkably, the number of households with female household heads in a municipality tends to increase as the regional microcredit operations increase, until reaching a peak in percentile 60 (3.27 pp). See Graph 4 (left).

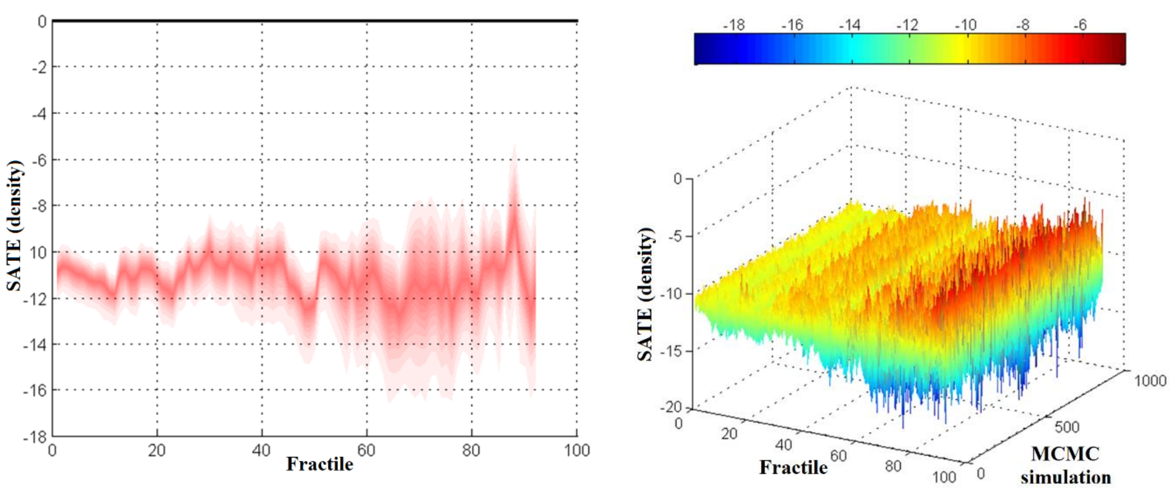
3) Informality. The evidence about informality suggests that the informal activities in the municipalities with access to microfinance are on average higher in the municipalities with local and medium levels of microfinance operations (below percentile 60), because when the intensity of microfinance operations increases above percentile 60, the SATE credibility intervals start to include zero (Graph 5, left). Nonetheless, this result has to be considered cautiously, because it is based on information of the household survey, which does not cover all Bolivian municipalities.

Table 1: Regional impact of microfinance in Bolivia*
(In percentage points)

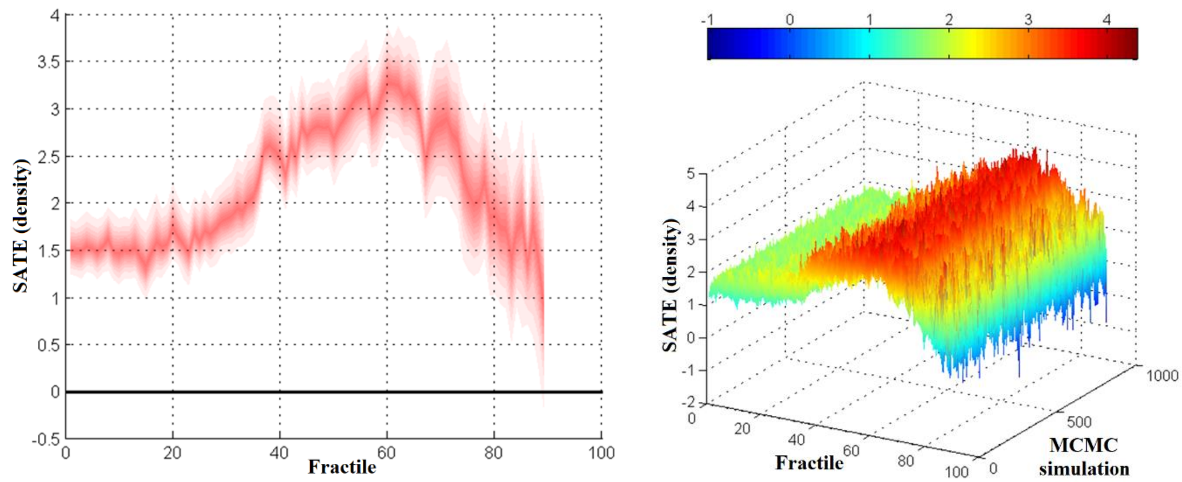
	Percentile 25	Percentile 50	Percentile 75
Poverty	-11.09 (-12.46; -9.81)	-12.35 (-14.25; -10.82)	-11.52 (-16.31; -7.86)
Empowerment of women	1.61 (1.27; 1.99)	2.68 (2.17; 3.19)	2.11 (1.28; 3.03)
Informality	7.55 (6.54; 8.77)	6.87 (4.13; 7.55)	6.04 (0.29; 9.74)

(*) Point estimation.
Between brackets below every estimator: confidence intervals at 95%.

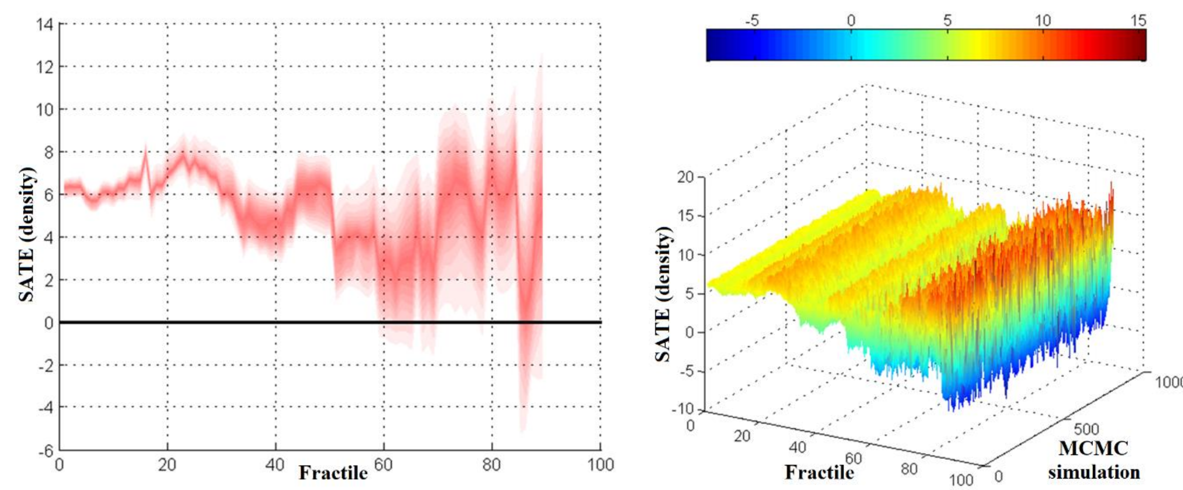
Graph 3: Spatial average treatment effect - poverty



Graph 4: Spatial average treatment effect – empowerment of women



Graph 5: Spatial average treatment effect - informality



With regard to the post-estimation validation (Table 2), the value of Efron's statistic pseudo-R^2, near 50%, shows an acceptable adjustment of the spatial probit model, the spatial correlation is greater in the models based on the household survey, and the balance test points to non-rejection of the null hypothesis of balancing of the control variables; nonetheless, the evidence on compliance of the balancing requirement is weaker for informality, which questions about the calculation of the score for this variable. The results of the Geweke convergence statistic (Geweke, 1992) show a good convergence of the MCMC in the case of variables poverty and the empowerment of women, but not in the case of informality, showing that it is necessary to be careful when interpreting the results in terms of the impact of microcredit on informality at the municipal level in Bolivia.

Table 2: Post-estimation statistics

	Poverty	Empowerment of women	Informality
Efron's pseudo-R^2			
R^2	52.26	52.02	45.56
Spatial correlation*			
ρ	0.155 (0.012; 0.321)	0.159 (0.012; 0.391)	0.462 (0.053; 0.88)
Estimation of the Spatial Probit model †			
x_0	-33.954	-34.429	-31.815
x_1	0.6644	0.6475	0.3816
x_2	0.3277	0.3307	0.3090
x_3	-0.0200	-0.0190	-0.0310
x_4	-0.027	-0.0270	-0.0240
x_5	0.0002	0.0001	0.0044
x_6	0.2213	0.2479	-1.0353
x_7	0.0095	0.0099	0.0024
x_8	0.2303	0.2342	0.2501
x_9	0.0279	0.0288	0.0367
Balancing Tests‡			
x_1	0.4691	0.4719	0.2424
x_2	0.1167	0.1148	0.0300
x_3	0.3434	0.3607	0.2001
x_4	0.0876	0.1010	0.0531
x_5	0.3685	0.3861	0.1183
x_6	0.0438	0.0473	0.0189
x_7	0.0487	0.0550	0.2074
x_8	0.1066	0.1027	0.0278
x_9	0.0671	0.0759	0.0261
Geweke's Convergence Diagnostic♦			
	0.4263	0.9512	0.0111

(*) Between brackets below each point estimator: credibility interval at 95%

(†) Bayesian point estimation. Term x_0 is the constant in the spatial model.

(‡) Bayesian P-values for the null hypothesis of balancing in the variable.

(♦) P-values for the null hypothesis of equality of the mean in the chain fractions. The test was performed in percentile 50 of the SATE chain and in fractions 10% and 50% at the beginning and end of the chain, respectively.

V. CONCLUSION

Gonzales et al. (2017) developed a quasi-experimental spatial algorithm for assessing the impact at the regional level. The algorithm was used to make an assessment of the impact of microcredit on poverty, informality and the empowerment of women in Bolivian municipalities.

Evidence was found in the sense that the municipalities with access to microcredit have a lower rate of poverty based on Unsatisfied Basic Needs (UBN) and have more households in which a woman is the household head, as the proxy variable of the empowerment of women in terms of decision-making. The results with regard to poverty reduction coincide with the ones found at the level of individuals and households by Wright (2000), Morduch and Haley (2002), or Khandker (2005), and the favorable effects on the empowerment of women are similar to those found by e.g. Rahaman (1986), Pitt and Khandker (1998), Pitt et al. (2006), or Swain and Wallentin (2009). Moreover, the results suggest that a possible cost of reducing poverty and fomenting the empowerment of women could have been an increase of informality, at least when microfinancing is incipient in a region. Considering that at present, the main criterion to access microcredit in Bolivia is the generation of income and the payment ability —beyond the evaluation of whether the applicant's economic activity has all legal documents for operation— the effect of microfinance may be a factor in addition to the structural factors that generate informality in the country, i.e. the regulatory burden, weak institutions and the lack of perceived benefits for being formal (World Bank 2009). However, the evidence of the relationship between microcredit and informality analyzed in this study is weak and cannot be considered conclusive because of the following reasons: (i) the information collected through the household surveys does not cover all municipalities of Bolivia, and (ii) no adequate balancing of the variables and no adequate convergence of the MCMC were observed during the BS-PSM estimation for the variable of informality.

In terms of policy recommendations, the results of the study are relevant to formulate evidence-based policies for Patriotic Agenda 2025 and Financial Services Law No. 393 of Bolivia. Pilar 5 of Bolivia's National Development Plan seeks to ensure comprehensive development of the financial system in support of poverty eradication by granting loans and other services. Law No. 393, on the other hand, is much more than a prudential regulation and seeks to improve the access to financial services for the benefit of the low-income population. Within the framework of this law, financial services must have a social function in conditions of equal treatment, non-discrimination on grounds of age, gender, race, religion or cultural identity.

The favorable impact of microcredit on poverty and the empowerment of women found in this study suggests that enhancing financial access and improving the granting of loans at the municipal level, primarily in municipalities with a limited or no presence of financing entities, can be helpful to accomplish the objectives of Law No. 393 and the Patriotic Agenda.

In order to be effective, these policies to improve access and quality of the financial services at the municipal level, must be underpinned by a local policy at the subnational level based on the identification of transmission mechanisms through which microfinance operates, particularly: (i) if the transmission channels are through changes in the roles assigned within the household, the incentivized policies should aim to give more power to women and offer financial education so that women could adequately administer their financial resources, (ii) if the channels are the companies of auxiliary industries, then it is necessary to strengthen the human resources and the institutions providing financial services in remote areas, and finally (iii) if the transmission is through local multiplier effects of an increased consumption, it may be that no other additional policies are required, since merely broadening the access to microcredit would reduce poverty and empower women in the region.

REFERENCES

Abadie, A. & Imbens, G. (2008). On the failure of the bootstrap for matching estimators. Econometrica, 76(6), 1537–1557.

Abadie, A. & Imbens, G. (2009). Matching on the estimated propensity score. NBER Working Papers 15301, National Bureau of Economic Research.

Albert, J. & Chib, S. (1993). Bayesian analysis of binary and polychotomous response data. Journal of the American Statistical Association, 88(422), 669–679.

Alvarez, M. & Levin, I. (2014). Uncertain neighbors: Bayesian propensity score matching for causal inference. Technical report, California Institute of Technology, University of Georgia.

An, W. (2010). Bayesian propensity score estimators: Incorporating uncertainties in propensity scores into causal inference. Sociological Methodology, 40(1), 151–189.

Anselin, L. (1988). Spatial econometrics: Methods and models. Volume 4. Springer.

Anselin, L. & Florax, R. (2011). New directions in spatial econometrics. Advances in spatial science. Springer Berlin Heidelberg.

Arbia, G. (2010). Spatial econometrics: Statistical foundations and applications to regional convergence. Advances in spatial science. Springer Berlin Heidelberg.

Banerjee, A., Karlan, D. & Zinman, J. (2015). Six randomized evaluations of microcredit: Introduction and further steps. American Economic Journal: Applied Economics, 7(1), 1-21.

Bateman, M. (2010). Why doesn't microfinance work? The destructive rise of local neoliberalism. Zed Books London-New York.

Bateman, M. (2013). The age of microfinance: Destroying Latin American economies from the bottom up. Working Papers 39. Austrian Foundation for Development Research.

Bauwens, L., Lubrano, M. & Richard, J. (2000). Bayesian inference in dynamic econometric models. Oxford University Press.

Brett, J. (2006). We sacrifice and eat less: The structural complexities of microfinance participation. Human Organization, 65(1), 8–19.

Caliendo, M. & Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. Journal of Economic Surveys, 22(1), 31–72.

Campos, J., Ericsson, N. & Hendry, D. (2005). General to specific modeling: an overview and selected bibliography. International Finance Discussion Papers 838, Board of Governors of the Federal Reserve System (U.S.).

Capello, R. (2009). Spatial spillovers and regional growth: A cognitive approach. European Planning Studies, 17(5), 639–658.

Chagas, A., Toneto, R. & Azzoni, C. (2011). A spatial propensity score matching evaluation of the social impacts of sugarcane growing on municipalities in Brazil. International Regional Science Review.

Chib, S. & Greenberg, E. (2010). Bayesian matching for causal inference. Technical report, Washington University in St. Louis, Yale University.

Chowdhury, A. & Bhuiya, A. (2004). The wider impacts of BRAC poverty alleviation programme in Bangladesh. Journal of International Development, 16(3), 369–386.

Chowdhury, A., Mushtaque, R., Mosley, P. & Simanowitz, A. (2004). The social impact of microfinance. Introduction. Journal of International Development, 16, 291-300.

Corrado, L. & Fingleton, B. (2012). Where is the economics in spatial econometrics? Journal of Regional Science, 52(2), 210–239.

De Castris, M. & Pellegrini, G. (2015). Neighborhood Effects On The Propensity Score Matching. Working Paper 05/5, CREI Università degli Studi Roma Tre.

Eclac (2009). Income poverty and unsatisfied basic needs. Project and research documents lc/mex/l.949, Economic Commission for Latin America and the Caribbean (ECLAC).

Economist Intelligence Unit (2010). Global microscope on the microfinance business environment 2010. Inter-American Development Bank.

Economist Intelligence Unit (2011). Global microscope on the microfinance business environment 2011. Inter-American Development Bank.

Elhorst, J. (2014). Linear spatial dependence models for cross section data. In Spatial Econometrics, Springer Briefs in Regional Science, pp. 5–36. Springer Berlin Heidelberg.

Efron, B. (1978). Regression and ANOVA with zero-one data: Measures of residual variation. Journal of the American Statistical Association, 73(361), 113–121.

Efron, B. (2013). Bayes' theorem in the 21st century. Science 340.

Gelman, A. & Hill, J. (2007). Data analysis using regression and multilevel/hierarchical models. New York: Cambridge University Press.

Gelman, A., Park, D., Ansolabehere, S., Price, P. & Minnite, L. (2001). Models, assumptions and model checking in ecological regressions. Journal of the Royal Statistical Society: Series A (Statistics in Society), 164(1), 101-118.

Geweke, J. (2005). Contemporary Bayesian Econometrics and Statistics. Wiley Series in Probability and Statistics. Wiley.

Geweke, J. (1992). Evaluating the accuracy of sampling-based approaches to the calculation of posterior moments. In Bayesian Statistics 4, eds. J. M. Bernardo, J. Berger, A. P. David, and A. F. M. Smith, Oxford, U.K.: Oxford University Press, pp. 169-193.

Gill, J. (2007). Bayesian methods: A social and behavioral sciences approach, 2nd ed. Chapman & Hall/CRC Statistics in the Social and Behavioral Sciences. Taylor & Francis.

Glennerster, R. & Takavarasha, K. (2013). Running randomized evaluations: A practical guide. Princeton University Press.

Gonzales, R. (2010). On the importance of credit for regional economic development in Bolivia: an analysis with non-parametric inference, spatial econometrics and Bayesian methods. Central Bank of Bolivia Research Award.

Gonzales, R. (2015). A natural-conjugate Bayesian version of the Smith-Todd balancing test. Technical Report 01/2015, Bayesian Institute for Research on Development.

Griffith, D. & Paelinck, J. (2011). Non-standard spatial statistics and spatial econometrics. Springer Science & Business Media.

Hendry, D. & Nielsen, B. (2007). Econometric modeling: a likelihood approach. Princeton University Press.

Hirano, K. & Imbens, G. (2004). The propensity score with continuous treatments. Applied Bayesian modeling and causal inference from incomplete-data perspectives, 2004, vol. 226164, p. 73-84.

Hoshino, T. (2008). A Bayesian propensity score adjustment for latent variable modeling and MCMC algorithm. Computational Statistics and Data Analysis, 52(3), 1413-1429.

Hu, A. (2017). Uncertainty of Statistical Models and Propensity Score Methods. Chinese Journal of Sociology. Vol. 37, No. 1.

Johnson, S. (2004). The impact of microfinance institutions in local financial markets: a case study from Kenya. Journal of International Development, 16(3), 501–517.

Khalily, M (2004). Quantitative approach to impact analysis of microfinance programs in Bangladesh: what have we learned? Journal of International Development, 16(3), 331–353.

Khandker, S. (2005). Microfinance and poverty: Evidence using panel data from Bangladesh. The World Bank Economic Review, 19(2), 263–286.

Kaplan, D. & Chen, J. (2012). A two-step Bayesian approach for propensity score analysis: Simulations and case study. Psychometrika, 77(3), 581-609.

Karlan, D. & Goldberg, N. (2007). Impact evaluation for microfinance: Review of methodological issues. World Bank, Poverty Reduction and Economic Management, Thematic Group on Poverty Analysis, Monitoring and Impact Evaluation.

Lesage, J. (2000). Bayesian estimation of limited dependent variable spatial autoregressive models. Geographical Analysis, 32(1), 19-35.

Lesage, J. & Pace, R. (2009). Introduction to spatial econometrics. Boca Raton (USA): Chapman-Hall.

Li, F., Zaslavsky, A. & Landrum, M. (2013). Propensity score weighting with multilevel data. Statistics in Medicine, 32(19), 3373-3387.

Link, W. & Eaton M. (2012). On thinning of chains in MCMC. Methods in Ecology and Evolution, 3(1), 112–115.

Mccandless, L., Gustafson, P., Austin, P. & Levy, A. (2009). Covariate balance in a Bayesian propensity score analysis of beta blocker therapy in heart failure patients. Epidemiologic Perspectives and Innovations, 6(1), 5.

Mknelly, B. & Dunford, C. (1999). Impact of credit with education on mothers and their young children’s nutrition: Crecer credit with education program in Bolivia. Freedom from Hunger Research Paper 5.

Mcintosh, C. (2008). Estimating treatment effects from spatial policy experiments: An application to Ugandan microfinance. The Review of Economics and Statistics, 90(1), 15–28.

Morduch, J. & Haley, B. (2002). Analysis of the effects of microfinance on poverty reduction. Technical report, NYU Wagner Working Paper

Mosley, P. (2001). Microfinance and poverty in Bolivia. Journal of Development Studies, 37(4), 101–132.

Mosley, P. (2003). Micro-insurance: scope, design and assessment of wider impacts. IDS bulletin, vol. 34, no 4, p. 143-155.

Mosley, P. & Rock, J. (2004). Microfinance, labour markets and poverty in Africa: a study of six institutions. Journal of International Development, 16(3), 467-500.

Navajas, S., Schreiner, M., Meyer, R., Gonzalez-Vega, C. & Rodriguez-Meza, J. (2000). Microcredit and the poorest of the poor: Theory and evidence from Bolivia. World Development, 28(2), 333–346.

Pitt, M. & Khandker, S. (1998). The impact of group-based credit programs on poor households in Bangladesh: Does the gender of participants matter? Journal of Political Economy, 106(5), 958–996.

Pitt, M., Khandker, S. & Cartwright, J. (2006). Empowering women with micro finance: Evidence from Bangladesh. Economic Development and Cultural Change, 54(4), 791–831

Rahman, R. (1986). Impact of Grameen bank on the situation of poor rural women. Grameen Bank Evaluation Project Working Paper 1.

Roodman, D. & Morduch, J. (2009). The impact of microcredit on the poor in Bangladesh: Revisiting the evidence. Center for Global Development Working Paper (174).

Rosenbaum, P. & Rubin, D. (1983). The central role of the propensity score in observational studies for causal effects. Biometrika, 70(1), 41-55.

Shalloway, D. (2014). The evidentiary credible region. Bayesian Analysis, 9(4), 909–922.

Smith, T. & Lesage, J. (2004). A Bayesian probit model with spatial dependencies. Advances in Econometrics, 18, 127–160.

Smith, J. & Todd, P. (2005). Rejoinder. Journal of Econometrics, 125(1-2), 365–375.

Swain, R. & Wallentin, F. (2009). Does microfinance empower women? Evidence from self-help groups in India. International Review of Applied Economics, 23(5), 541–556.

Van De Schoot, R., Broere, J., Perryck, K., Zondervan-Zwijnenburg, M. & Van Loey, N. (2015). Analysing small data sets using Bayesian estimation: the case of posttraumatic stress symptoms following mechanical ventilation in burn survivors. European Journal of Psychotraumatology, Vol. 6.

Velasco, C. & Marconi, R. (2004). Group dynamics, gender and microfinance in Bolivia. Journal of International Development, 16(3), 519–528.

Warren, S., Fey, M. & Yoder, P. (2007). Differential treatment intensity research: A missing link to creating optimally effective communication interventions. Mental Retardation and Developmental Disabilities Research Reviews, 13(1), 70–77

Weiss, J. & Montgomery, H. (2005). Great expectations: microfinance and poverty reduction in Asia and Latin America. Oxford Development Studies, 33(3-4), 391-416.

World Bank (2009). Increasing formality and productivity of Bolivian firms. Country Studies. World Bank.

Wright, G. (2000). Microfinance systems: Designing quality financial services for the poor. Zed books London.

Wright, K. & Copestake, J. (2004). Impact assessment of microfinance using qualitative data: communicating between social scientists and practitioners using the quip. Journal of International Development, 16(3), 355–367.

Yogendrarajah, R. (2013, December). Women Empowerment through Decision Making. The International Journal of Economics and Business Management, 3(1).

Zigler, C. (2016). The Central Role of Bayes' Theorem for Joint Estimation of Causal Effects and Propensity Scores. The American Statistician, 70(1), 47–54.

Zigler, C. & Dominici, F. (2014). Uncertainty in propensity score estimation: Bayesian methods for variable selection and model-averaged causal effects. Journal of the American Statistical Association, 109(505), 95–107.

Zohir, S. & Matin, I. (2004). Wider impacts of microfinance institutions: issues and concepts. Journal of International Development, vol. 16, No. 3, p. 301-33.

ANNEX 1

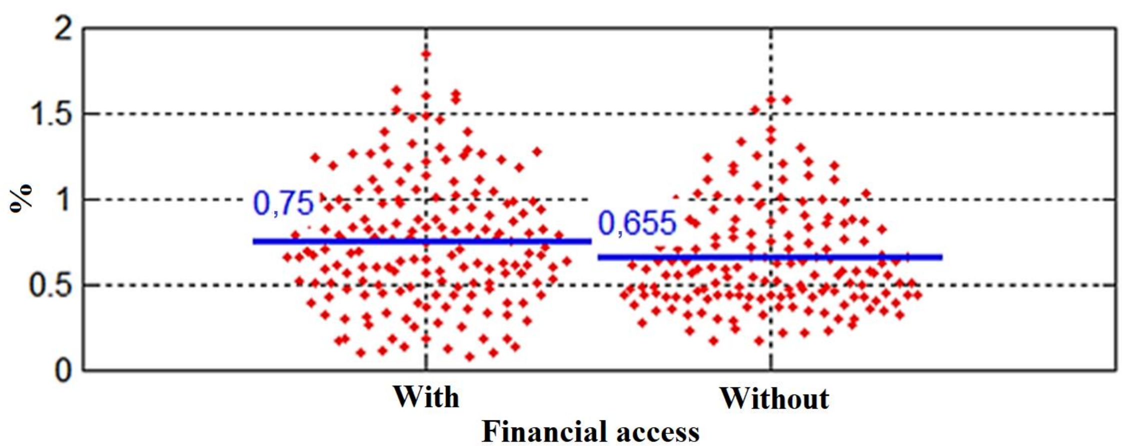
FALSIFICATION TEST OF THE BS-PSM ALGORITHM

A falsification test has been performed concerning BS-PSM algorithm with the aim of evaluating whether it falsely detects regional impacts. The falsification hypothesis is that there is a causal relationship between microcredit and the percentage of deaf people in a municipality, whereby this assertion is most probably untrue and should therefore be rejected by the algorithm.

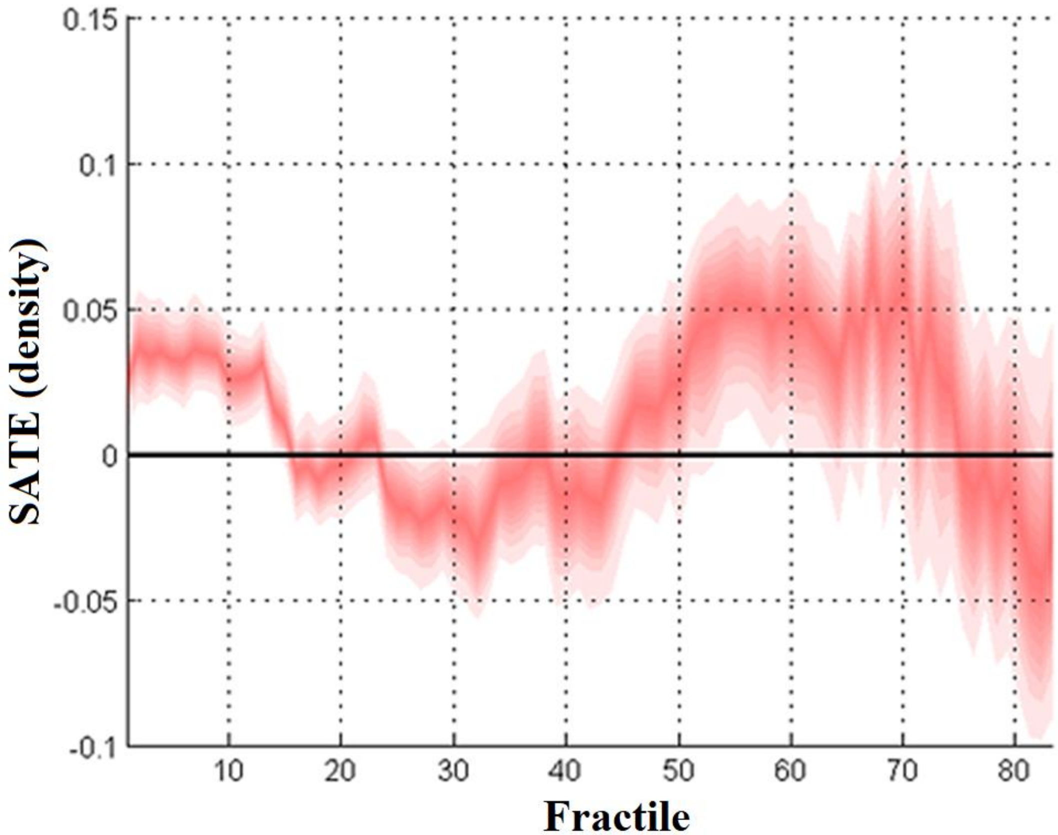
Graph A.1 shows the differences observed with regard to the individuals suffering from deafness in the municipalities with and without access to microfinance, without controlling for idiosyncratic variables; the census data show that there is a greater percentage of deaf people in municipalities without access to microfinance (75%) compared to the municipalities with access to microfinance (65%).

Graph A.2 shows the results of the Bayesian estimation, based on algorithm BS-PSM. With a credibility level of 95%, estimator BS-PSM is near zero, which does not provide any evidence in favor of the initially stated falsification hypothesis. The lack of confirmation of the improbable link between microfinance and people suffering from deafness, supports the validity of BS-PSM algorithm and reinforces the conclusions about the associations of interest in the study.

Graph A.1: Differences observed between people with deafness and municipalities with and without access to microfinance



Graph A.2: Average differences of municipalities with and without access to microfinance, estimated using BS-PSM



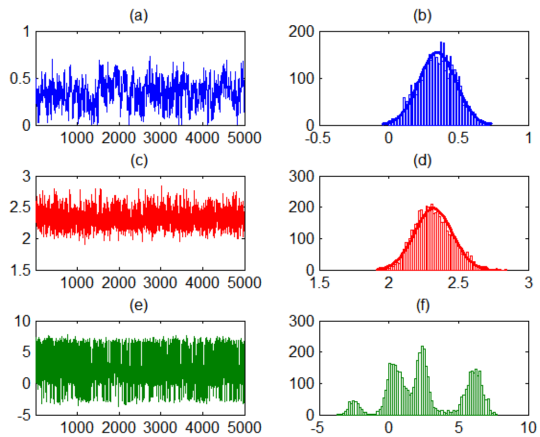
ANNEX 2

ANALYSIS OF ROBUSTNESS OF THE RESULTS IN RESPONSE TO CHANGES IN THE MATCHING TECHNIQUE AND THE EXCLUSION OF SPATIAL EFFECTS

Robustness of the results in response to the exclusion of spatial information was evaluated by changing the hyperparameter of the spatial correlation coefficient of the probit function to $\rho \sim \mathcal{U}(-1;0,1)$ so it would not include any spatial correlation (in the study, the assumption was $\rho \sim \mathcal{U}(0,1)$, i.e. an a priori positive spatial correlation). On the other hand, the robustness of the results in response to changes in the matching technique was evaluated by using nearest neighbor matching instead of the spatial caliper matching technique.

As a result of the new prior ρ, the posterior estimation of ρ includes zero with a probability of 95% (graphs A.4b, A.6b and A.8b), in other words, there is no spatial correlation in the probit model used to estimate the matching scores. The SATE estimations based on this assumption of no spatial correlation are not affected by this hypothesis, since the results with and without spatial information are almost the same, as can be observed in graphs A.3d, A.4d, A.5d, A.6.d, A.7d and A.8.d. On the other hand, the estimation based on non-spatial nearest neighbor matching produces a multimodal estimation of the regional ATE. This last result suggests that the SATE estimation is robust to the inclusion/exclusion of spatial effects during the matching, but not to the estimation of the matching probabilities in the discrete choice model. See graph A.3d compared to A.3f, A.4d against A.4f, A5d against A.5f, A.6d against A.6f, A.7d against A.7f and A.8d against A.8f.

Graph A.3: SATE estimation for the empowerment of women with spatial information



(a) MCMC estimation of $\hat{\rho}$ with prior $\rho \sim \mathcal{U}(0,1)$.

(b) Histogram of $\hat{\rho}$.

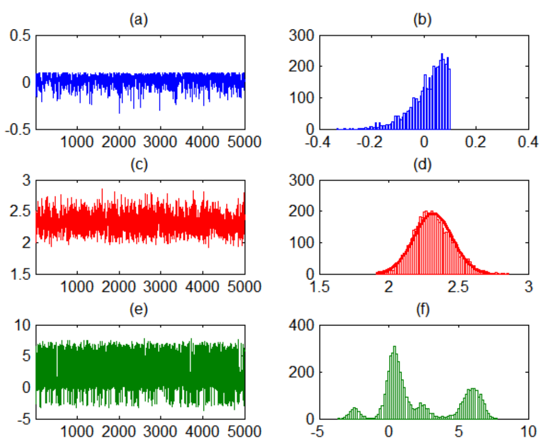
(c) MCMC estimation of SATE with spatial matching.

(d) SATE histogram with spatial matching.

(e) MCMC estimation of SATE without spatial matching.

(f) SATE histogram without spatial matching.

Graph A.4: SATE estimation for the empowerment of women without spatial information



(a) MCMC estimation of $\hat{\rho}$ with prior $\rho \sim \mathcal{U}(-1;0,1)$.

(b) Histogram of $\hat{\rho}$.

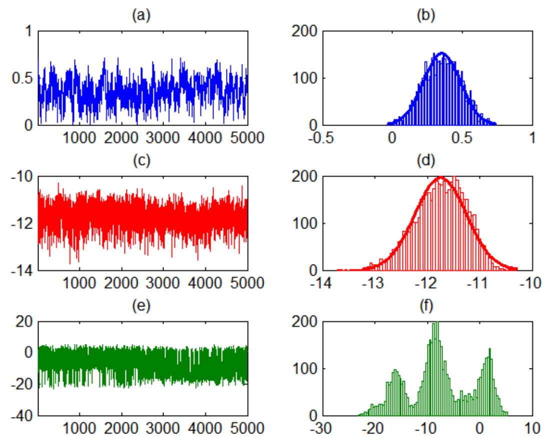
(c) MCMC estimation of SATE with spatial matching.

(d) SATE histogram with spatial matching.

(e) MCMC estimation of SATE without spatial matching.

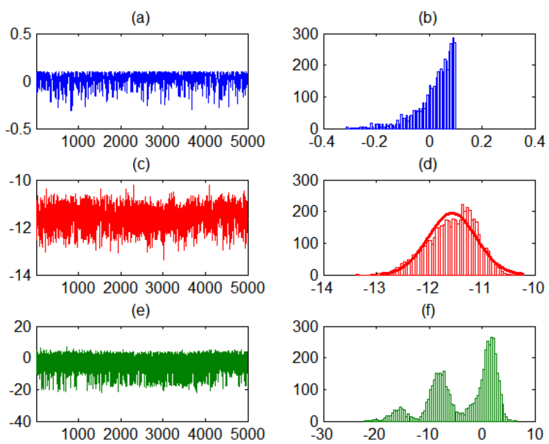
(f) SATE histogram without spatial matching.

Graph A.5: SATE estimation for poverty with spatial information



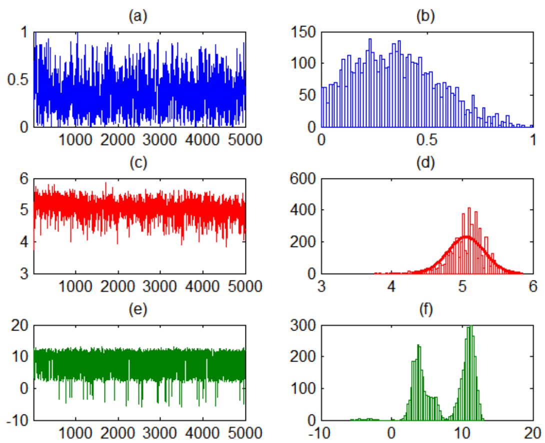
(a) MCMC estimation of $\hat{\rho}$ with prior $\rho \sim \mathcal{U}(0,1)$.
(b) Histogram of $\hat{\rho}$.
(c) MCMC estimation of SATE with spatial matching.
(d) SATE histogram with spatial matching.
(e) MCMC estimation of SATE without spatial matching.
(f) SATE histogram without spatial matching.

Graph A.6: SATE estimation for poverty without spatial information



(a) MCMC estimation of $\hat{\rho}$ with prior $\rho \sim \mathcal{U}(-1;0,1)$.
(b) Histogram of $\hat{\rho}$.
(c) MCMC estimation of SATE with spatial matching.
(d) SATE histogram with spatial matching.
(e) MCMC estimation of SATE without spatial matching.
(f) SATE histogram without spatial matching.

Graph A.7: SATE estimation for informality with spatial information



(a) MCMC estimation of $\hat{\rho}$ with prior $\rho \sim \mathcal{U}(0,1)$.

(b) Histogram of $\hat{\rho}$.

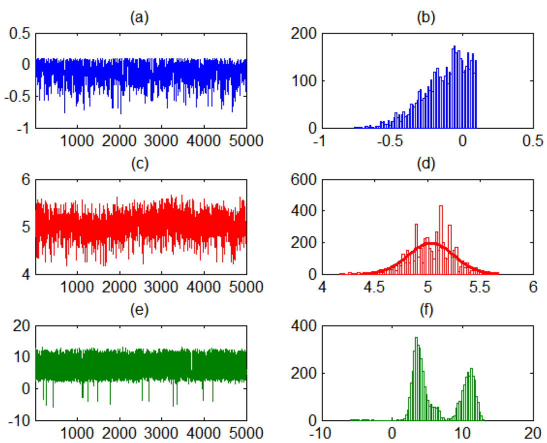
(c) MCMC estimation of SATE with spatial matching.

(d) SATE histogram with spatial matching.

(e) MCMC estimation of SATE without spatial matching.

(f) SATE histogram without spatial matching.

Graph A.8: SATE estimation for informality without spatial information



(a) MCMC estimation of $\hat{\rho}$ with prior $\rho \sim \mathcal{U}(-1;0,1)$.

(b) Histogram of $\hat{\rho}$.

(c) MCMC estimation of SATE with spatial matching.

(d) SATE histogram with spatial matching.

(e) MCMC estimation of SATE without spatial matching.

(f) SATE histogram without spatial matching.