A Bayesian Spatial-Propensity Score Matching Evaluation of the Regional Effects of Microfinance in Bolivia*

Rolando Gonzales[†], *Patricia Aranda*[‡], *Joel Mendizabal*

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Abstract

A Bayesian spatial-propensity score matching estimator is proposed to measure regional treatment effects. The regional effects of microfinance in Bolivia were tested with this estimator, using census and household survey data. The results suggest that microfinance was useful for poverty reduction and women-empowerment at municipality level in Bolivia, with the possible cost of increasing informality.

Keywords: Microfinance, regional effects, Bayesian methods, spatial statistics, matching estimators
JEL codes: C11, C31, G21

1 Introduction

A Bayesian spatial-propensity score matching (BS-PSM) estimator to measure regional (spatial) effects is proposed. PSM allows for controlling selection bias through the estimation of the probabilities of receiving treatment, given some observed covariates. At regional level, the probability of belonging to a group is influenced by the proximity to other regions. Furthermore, the dynamics of one local economy influence neighboring local economies, through trade linkages and market relationships—as demand linkages and interregional mobility of production factors—, with a level of influence spatially-bounded by the distance between regions (Capello, 2009). Thus, spatial effects need to be taken into account when estimating the scores used for matching.

Bayesian alternatives to frequentist PSM have recently been proposed[1] and spatial propensity score matching was used by Chagas et al. (2011) but, to our knowledge, a spatial matching estimator was never constructed from a Bayesian perspective before[2]. As propensity score matching is a two-stage estimation technique, the standard error of the Average Treatment Effect (ATE) needs to be adjusted to account for the uncertainty in the first-stage estimation of the propensity score (Gelman and Hill, 2007). Abadie and Imbens (2009) proposed a downward adjustment of the variance of the ATE based on the fact that the ATE estimate and the parameters of the propensity score model are jointly normal asymptotically. Nevertheless, the Abadie-Imbens method is valid only for large samples and has the drawback of producing a negative adjusted variance in some cases (An, 2010). Also,

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[†]Bayesian Institute for Research on Development (BayesGroup.org). Contact: rgonzales@bayesgroup.org

[‡]Supervisory authority of the financial system in Bolivia (ASFI). Contact: paranda@asfi.gob.bo

[1]See *inter alia* Hoshino (2008), McCandless et al. (2009), Chib and Greenberg (2010), An (2010), Kaplan (2012), Alvarez and Levin (2014), or Zigler (2014).

[2]Searching in Google Scholar, we found 29300 results for «Propensity Score Matching» 28 for «Spatial Propensity Score Matching» and 10 for «Bayesian Propensity Score Matching», but no results were obtained when searching for «Spatial Bayesian Propensity Score Matching».

even if bootstrap might look like a natural candidate to estimate the cumulative distribution function of ATE due to consistency theorems—see Horowitz (2001)—Abadie and Imbens (2008) showed also that bootstrap is not valid for calculating the standard errors of matching estimators, even in the simple case with a single continuous covariate. Thus, compared with variance adjustment methods, a Bayesian approach guarantees positive standard errors, is more reliable in small samples and can be readily employed to draw inference on regional treatment effects, because with Bayesian methods it is possible to estimate the complete posterior distribution of the ATE, thus naturally incorporating uncertainties into causal inference.

The BS-PSM estimator was used to evaluate the overall regional effects of microfinance in Bolivia. Microfinance is the provision of small-scale financial services to low-income clients who lack access to traditional banking services (Karlan and Goldberg, 2007). Overall regional effects of microfinance arise when the impact of microfinancial access spreads out beyond target clients and towards other economic agents within the same geographical unit and/or neighboring units: due to the socio-economic interaction between the recipients of microfinancial services and the non-participant population, microfinance can indirectly affect people without microfinancial access through spillovers. Studies as Velasco and Marconi (2004) or Gonzales (2010) analyzed the wider impacts of microfinance access in Bolivia before, but did not performed a rigorous impact evaluation; as BS-PSM is a spatial quasi-experimental design for impact evaluation, it is a methodological improvement over past studies.

Section 2 describes the BS-PSM estimator. Section 3 presents an application for the Bolivian case. Section 4 discusses the results. The MatLab code to replicate the results is available upon request.

2 Bayesian Spatial PSM estimator

Spatial probit models. Let $\mathbf{y}$ be a $n \times 1$ vector of 0,1 binary values that reflect the absence/presence of a treatment in a region $i = 1, \ldots, n$. In,

$$\mathbf{y} = \rho \mathbf{W}\mathbf{y} + \mathbf{X}\beta + \epsilon, \qquad \epsilon \sim \mathcal{N}\left(0, \sigma_\epsilon^2 \mathbf{I}_n\right) \tag{1}$$

ρ is a spatial correlation coefficient, $\mathbf{W}$ is a $n \times n$ row-stochastic proximity matrix and $\mathbf{X}$ is $n \times p$ a matrix of p control covariates,

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

Equation (1) is a Spatial Auto-Regressive (SAR) model and, despite its linear appearance, is a highly non-linear model, as,

$$\begin{aligned} \mathbf{y} &= \rho \mathbf{W}\mathbf{y} + \mathbf{X}\beta + \epsilon, \\ (\mathbf{I} - \rho\mathbf{W})\mathbf{y} &= \mathbf{X}\beta + \epsilon, \\ \mathbf{y} &= (\mathbf{I} - \rho\mathbf{W})^{-1}\mathbf{X}\beta + (\mathbf{I} - \rho\mathbf{W})^{-1}\epsilon, \end{aligned}$$

and if $|\rho| < 1$ then,

$$(\mathbf{I} - \rho\mathbf{W})^{-1} = \mathbf{I} + \rho\mathbf{W} + \rho^2\mathbf{W}^2 + \rho^3\mathbf{W}^3 + \cdots$$

On the other hand, in a Spatial Error Model (SEM), the spatial influence comes only through the error term,

$$\begin{cases} \mathbf{y} = \mathbf{X}\beta + \epsilon, \\ \epsilon = \rho\mathbf{W}\epsilon + \nu, \qquad \nu \sim \mathcal{N}\left(0, \sigma_\nu^2 \mathbf{I}_n\right) \end{cases} \tag{2}$$

In the case of the SAR model, the spatial lag $\mathbf{Wy}$ has a substantive interpretation related to the existence of spatial interactions among neighboring regions in the dependent variable $\mathbf{y}$ with an intensity of cross-regional effects captured by ρ[3]. The SEM model in turns is consistent with a situation where unobserved shocks in the error term are spatially autocorrelated (Elhorst, 2014) and thus failing to acknowledge their presence leads to biased inference, can be a cause of inconsistent estimation, and leads to an incorrect understanding of true causal processes.

The Bayesian latent variable treatment for modeling this type of spatial limited dependent variables treats the binary 0,1, observations in $\mathbf{y}$ as indicators of a latent, unobserved (net) utility of a spatial agent in a i-region. Formally, based on the difference in utilities $\mathcal{U}_{1i} - \mathcal{U}_{0i}$, $i = 1, \ldots, n$ associated with observed 0,1 choice indicators, the probit model assumes that the difference $\mathbf{y}_i^* = \mathcal{U}_{1i} - \mathcal{U}_{0i}$ follows a Gauss-Laplace distribution, and, as $\mathbf{y}_i^*$ is unobservable, then $y_i = 1$ if $\mathbf{y}_i^* \geq 0$ and $y_i = 0$ if $\mathbf{y}_i^* < 0$. This implies $\mathbb{P}(y_i = 1) = \mathbb{P}(\mathcal{U}_{1i} \geq \mathcal{U}_{0i}) = \mathbb{P}(y_i^* \geq 0)$; see Smith and LeSage (2004)

[3]In the present study, the spatial lag $\mathbf{Wy}$ captures the idea that the existence of financial institutions in one region affect the existence of financial instituions in other regions, in the sense that the location of one or more financial institutions in a municipality affects the decision of locating financial institutiones in neighboring regions, in a negative or positive way.

for a detailed discussion on the Bayesian latent variable treatment of probit models.
In the SAR probit model the latent variable follows a multivariate truncated gaussian distribution,

$$\mathbf{y}^* \sim \mathcal{TMVN}\left(\mu, \mathbf{\Sigma}\right),$$

with,

$$\mu = \left(\mathbf{I}_n - \rho\mathbf{W}\right)^{-1}\mathbf{X}\beta,$$

and

$$\mathbf{\Sigma} = \left(\left(\mathbf{I}_n - \rho\mathbf{W}\right)'\left(\mathbf{I}_n - \rho\mathbf{W}\right)\right)^{-1}.$$

A Markov Chain Monte Carlo (MCMC) sampler for the SAR probit model can be implemented with a prior $\pi(\beta,\rho) = \pi(\beta)\pi(\rho)$, where $\beta \sim \mathcal{N}(c, T)$ and $\rho \sim \mathcal{U}(a, b)$, and thus the posterior densities are,

$$\begin{aligned}
\mathbb{P}(\beta|\rho, y^*) &\propto \mathcal{N}(c^*, \mathbf{T}^*),\\
c^* &= \left(\mathbf{X}'\mathbf{X} + \mathbf{T}^{-1}\right)^{-1}\left(\mathbf{X}'\mathbf{S}\mathbf{y}^* + \mathbf{T}^{-1}c\right)^{-1},\\
\mathbf{T}^* &= \left(\mathbf{X}'\mathbf{X} + \mathbf{T}^{-1}\right)^{-1},\\
\mathbf{S} &= \left(\mathbf{I}_n - \rho\mathbf{W}\right),
\end{aligned}$$

and

$$\mathbb{P}(\rho|\beta, y^*) \propto |\mathbf{I}_n - \rho\mathbf{W}| \exp\left(-\frac{1}{2}\left(\mathbf{S}y^* - \mathbf{X}\beta\right)'\left(\mathbf{S}y^* - \mathbf{X}\beta\right)\right)$$

A similar treatment exist for SEM models. See LeSage and Pace (2009) for details.

Matching. All matching estimators contrast the outcome of a treated individual—a region, in this case—with outcomes of comparison group members (Caliendo and Kopeinig, 2008). The most straightforward matching estimator is nearest neighbor (NN) matching, in which a region from the comparison group is chosen as a matching partner for a treated region that is closest in terms of propensity score. Let $\hat{p} := \mathbb{P}(y_i = 1) = f(\hat{\rho}\mathbf{W}\mathbf{y}, \mathbf{X}\hat{\beta})$ be the estimated probabilities of a spatial probit model. A traditional pairwise nearest-neighbor matching between treated and untreated regions can be implemented with,

$$\mathcal{C}_{nn}\left(\hat{p}\right) = \min_j \|\hat{p}_i - \hat{p}_j\|, \qquad j \in n_0,$$

where n_0 denotes the set of untreated regions (i.e. those without financial access). In this type of matching the score of a i-treated region is compared with the scores of all the j-untreated regions in order to find a single untreated region with a similar score. NN matching faces the risk of bad matches, if the closest neighbour is far away (Caliendo and Kopeinig, 2008). This can be avoided by imposing a tolerance level on the maximum propensity score distance, i.e. a caliper: let δ be a proximity measure among regions—captured through the distance matrix $\mathbf{W}$—, if δ is considered when performing the matching,

$$\mathcal{C}_{sc}\left(\hat{p}, \mathbf{W}\right) = \min_j \|\hat{p}_i - \delta_j\hat{p}_j\|, \qquad j \in n_0,$$

the propensity score $\hat{p}_i$ of a i-treated region is compared only with the propensity scores of nearby untreated regions: δ_j is a binary vector with entries equal to one for the j-untreated regions geographically close to the treated region i, and zero in other cases. This is a type of *spatial caliper matching* (SCM), where the tolerance (the caliper) is given by the geographical proximity among regions. Applying a caliper matching means that those regions from the comparison group are chosen as a matching partner for a treated region that lies within the caliper and are closest in terms of propensity score (Caliendo and Kopeinig, 2008).
SCM is a type of spatial nearest-neighbor matching that compares the outcome of a i-treated region with that of the single closest untreated region (the one minimizing the distance $\|\hat{p}_i - \delta_j\hat{p}_j\|, j \in n_0$). Bad matches are not necessarily avoided with SCM if the closest neighbor still has a large distance in terms of both geographical distance and the difference between propensity scores. To avoid this problem, it is possible to compare an i-treated region with all its surrounding untreated regions,

$$\mathcal{C}_{sr}\left(\hat{p}, \mathbf{W}\right) = \|\hat{p}_i - \delta_j\hat{p}_j\|, \qquad j \in n_0.$$

This strategy gives rise to a *spatial radius matching* (SRM) which reduces the risk of bad matching by using more information to construct the counterfactual for each i-region (i.e. oversampling).

Spatial Average Treatment Effect (SATE). The spatial (regional) average treatment effect (SATE) is,

$$\begin{aligned}
\text{SATE} &:= \vartheta_u,\\
&= \mathcal{M}\left(\mathbf{O}, \mathbf{y}, \mathbf{W}, \mathbf{X}, \Theta\right),\\
&= \mathbb{E}\left\{(O_i|y_i = 1, X_{1i} = x_1, \ldots, X_{pi} = x_p)\right.\\
&\qquad \left. - (O_i|y_i = 0, X_{1i} = x_1, \ldots, X_{pi} = x_p)\right\},
\end{aligned}$$

for a regional outcome variable O, $\mathcal{M}(\cdot)$ a matching function and $\{\beta, \rho\} \in \Theta$ a stacked vector of parameters of the spatial model.

Density estimation of the SATE. Let $\left\{\hat{p}^{(1)}, \ldots, \hat{p}^{(g)}\right\}$ be g-estimated probabilities based on the g draws from

$\mathbb{P}(\beta^{(g)}|\rho, y^*) \propto \mathcal{N}(c^{*(g)}, \mathbf{T}^{*(g)})$ and $\mathbb{P}(\rho^{(g)}|\beta^{(g)}, y^*)$ in the spatial probit model, thus,

$$\mathcal{C}\left(\hat{p}^{(g)}\right) = \min_j \|\hat{p}_i^{(g)} - \hat{p}_j^{(g)}\|, \qquad j \in n_0,$$

and,

$$\mathcal{C}_{sc}\left(\hat{p}^{(g)}, \mathbf{W}\right) = \min_j \|\hat{p}_i^{(g)} - \omega_j \hat{p}_j^{(g)}\|, \qquad j \in n_0,$$
$$\mathcal{C}_{sr}\left(\hat{p}^{(g)}, \mathbf{W}\right) = \|\hat{p}_i^{(g)} - \omega_j \hat{p}_j^{(g)}\|, \qquad j \in n_0,$$

depending on the matching technique. The full density of the SATE can be estimated with the $g = 1, \ldots, G$-runs of the MCMC sampler,

$$\left\{\mathcal{M}\left(\mathbf{O}, \mathbf{y}, \mathbf{W}, \mathbf{X}, \Theta^{(g)}\right)\right\}_{g=1}^{G}.$$

See *inter alia* Chib and Greenberg (2010) or Alvarez and Levin (2014).

Point estimators and credible intervals. Let ϑ be a weighted/unweighted SATE estimator, $\vartheta \in \{\vartheta_u, \vartheta_\omega\}$. A Bayesian point estimator of the SATE $\hat{\vartheta}$ is the value of ϑ that minimizes the expected value of a loss function $L(\hat{\vartheta}, \vartheta)$, where the expectation is taken over the posterior distribution of ϑ, $\pi(\vartheta|\mathcal{D})$,

$$\min_{\hat{\vartheta}} \mathbb{E}[L(\hat{\vartheta}, \vartheta)] = \min_{\hat{\vartheta}} \int L(\hat{\vartheta}, \vartheta)\pi(\vartheta|\mathcal{D})d\vartheta.$$

Under quadratic loss, $L(\hat{\vartheta}, \vartheta) := \left(\hat{\vartheta} - \vartheta\right)^2$,

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

Differentiating with respect to $\hat{\vartheta}$ and setting the derivative equal to zero,

$$\hat{\vartheta} = \int \vartheta\pi(\vartheta|\mathcal{D})d\vartheta = \mathbb{E}(\vartheta|\mathcal{D}),$$

i.e. the optimal point estimator under quadratic loss is the mean of the simulated posterior distribution of ϑ. A Bayesian γ-credible interval $\mathbb{C}_{\vartheta,\gamma}$ for the SATE with a credibility $\gamma = 1 - \alpha$ can be obtained with a subregion of the probability space parameterized by $\vartheta \in \Theta$, where,

$$\int_{\mathbb{C}_{\vartheta,\gamma}} \pi(\vartheta|\mathcal{D})d\vartheta = \gamma.$$

3 Application: Regional effects of Microfinance in Bolivia

Data and variables. Access to microfinance was measured with the scaled number of micro-finance operations in a municipality of Bolivia. Let $\aleph_i$ be the number of micro-finance operations in a i-municipality of Bolivia, divided by the economically active population of this municipality. The binary variable y_i, $i = 1, \ldots, n$ in the vector of financial access $\mathbf{y}$ is equal to,

$$y_i = \begin{cases} 1 \text{ if } \aleph_i \geq \mathcal{Q}, \\ 0 \text{ if } \aleph_i < \mathcal{Q}, \end{cases}$$

for a threshold $\mathcal{Q} \in \mathbb{R}^+$. This strategy allows measuring the effects of *differential treatment intensities*, i.e. the differences in impact related to the quantity of microfinance operations delivered in a municipality.
The 339×9 matrix of variables $\mathbf{X}$ is composed of 9 variables for the 339 municipalities of Bolivia:

1. Population in the municipality.
2. Potential labor supply, measured as the percentage of the population of working age (15 and over) with respect to total population (it shows the percentage of people who offer and could offer their labor in the labor market)
3. Poor garbage disposal: as a proxy of living conditions. This variable was measured as the percentage of the households in a municipality which do not use the public collection service (the dump truck) or dump their garbage in a public container but instead burn/bury the garbage or throw it up in the street/in a river.
4. Place where women gave birth, different from health facilities: again a proxy of living conditions which should be (at least weakly) exogenous.
5. Percentage of people living in rural areas.
6. Percentage of households with access to electricity.
7. Percentage of children in the population.
8. Global participation rate of women, an employment indicator that is constructed to quantify the relative size of the work force and is calculated as the division of the economically active population between the working age population.

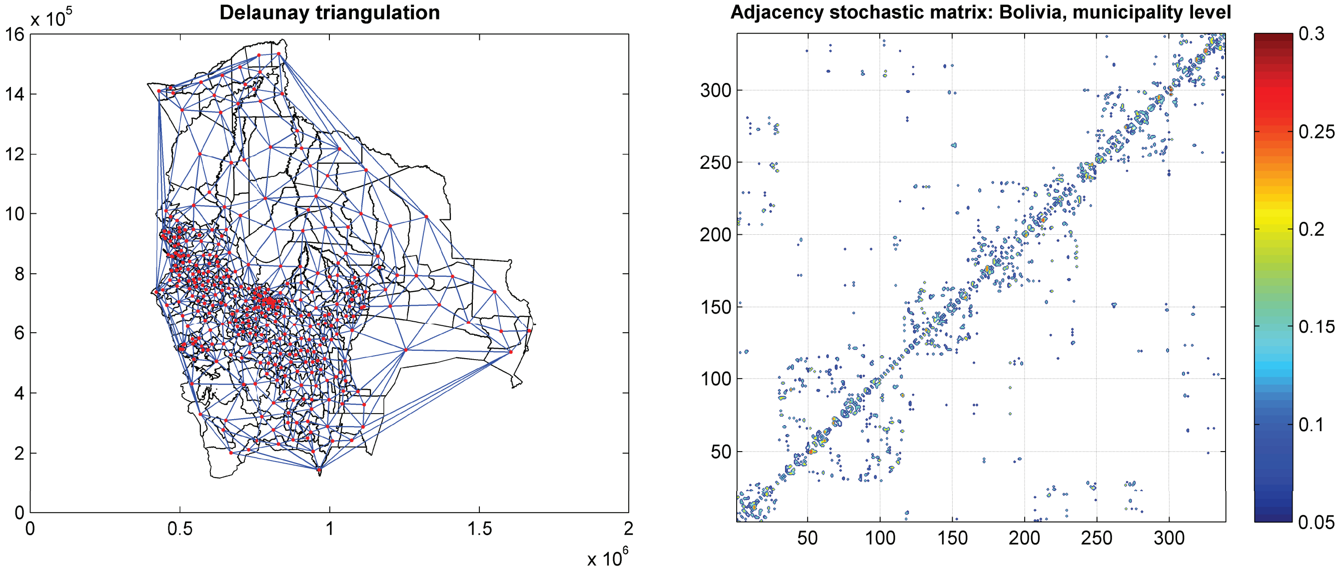

Figure 1: Delaunay triangulation and adjacency matrix

9. Educational units per capita, measured as the number of educational institutions in a municipality divided by the number of people living in the municipality.

These variables where selected from a large set (a General Unrestricted Model, GUM) using a general-to-specific modelling approach; see for example Campos et al. (2005). Variables (1) to (8) were calculated with the public information from the 2012 National Census of Population and Household of Bolivia; (9) is based on administrative records. As the data is from a census, no expansion factors were used during the estimation. Four outcome variables (**O**) were considered to account for the impact of microfinance at municipality level:

1. Poverty: measured with the Unsatisfied Basic Needs (UBN) method. UBN is a multidimensional measure of poverty which takes into account variables as quality of housing, household population density, access to potable water, access to adequate sanitation, education, insurance, electricity and household consumption capacity; see ECLAC (2009).
2. Unemployment: Unemployment rates were calculated from the information of the 2012 Census of Population and Housing. The indicator is calculated as the sum of the unemployed population with respect to the economically active population in a municipality.
3. Informality: lack of registration in the pension system was used as a proxy of informality, based on the records of the principal activity of the household head in the 2012 household survey of Bolivia. This legalistic definition of informality was previously used by the World Bank (2009) to analyze the reasons and the impact of informality in Bolivia.
4. Female Empowerment: the variable female empowerment at municipality level is defined as the proportion of female-headed households in a municipality which are not separated, divorced or widowed. This variable measures women empowerment through decision making at household level, as women are female-households even in the presence of a husband or partner in the household. A similar measure of empowerment was used by Yogendrarajah (2013).

Proximity matrix W. Based on the GIS shape file of Bolivia for the year 2012, an array of the proximity between the municipalities of Bolivia was obtained (*i*) choosing a regional breakdown, (*ii*) estimating the centroids of the regional polygons, and (*iii*) calculating the Euclidean distance between the centroids (in order to fulfill the Delauney triangulation condition). Figure 1 shows the result of using this procedure to calculate the proximity matrix of Bolivia, at municipality level. The resulting proximity matrix is a 339×339 square matrix $\mathbf{W}$.

Observed differences at municipality level. Figure 2 and Table 1 show the observed differences in outcomes among municipalities with and without financial access, for four levels of treatment intensity:

- $\mathcal{Q}_0$: treated municipalities were defined as the ones with at least one microfinance lending operation in 2012.
- $\mathcal{Q}_1$, $\mathcal{Q}_2$, $\mathcal{Q}_3$: treated municipalities are defined as those where microfinance lending operations scaled by the economically active population were higher than the first quintile (0.0063), the second quintile (0.0417) or the third quintile (0.0909) of $\aleph_i$ in 2012.

On average, poverty is higher in municipalities without access to microfinance, for all the levels of microfinance treatment. Informality is around 5% higher in municipalities with access to microfinance, and the percentage of female-household heads is close to 3% higher on average in the municipalities of Bolivia with access to microfinance. The difference of unemployment between municipalities with and without access to microfinance is close to zero.

Despite what the descriptive results may suggest, other demographic and socio-economic variables are relevant to explain the differences at municipality level among groups; thus, it is necessary to account for confounding variables to perform an unbiased impact evaluation of the overall regional effects of microfinance in Bolivia.

SATE with SAR and SEM spatial probit models. The Bayesian Spatial-Propensity Score Matching (BS-PSM) methods of Section 2 were used to take into account control covariates and spatial factors when estimating the *conditional* difference between *similar* municipalities of Bolivia, with and without microfinance access, for the four levels of microfinance treatment $\mathcal{Q}_0$, $\mathcal{Q}_1$, $\mathcal{Q}_2$, $\mathcal{Q}_3$. The estimated probabilities of receiving treatment ($\hat{p}$), given the observed variables $\mathbf{X}$ were used to match municipalities with similar probabilities of receiving the treatment. The difference between these matched municipalities was used to estimate the conditionally independent average regional effect of microfinance at municipality level in Bolivia, i.e. the Spatial Average Treatment Effect (SATE)[4].

Figures 3, 4, 5, 6 and Tables 2, 3, 4, 5 show the results of using BS-PSM to estimate the effects of microfinance in Bolivia at municipality level. In general, when the spatial distance among treated regions and counterfactuals is not explicitely taking into account during the matching (i.e. when using NNM) the results tend to be erratic for all the outcomes, possibly due to bad matches among regions. In contrast, taking into account geographical closeness among regions (using SCM) or comparing geographically contiguous regions (using SRM) produces more stable results for each treatment intesity. The amplitude of the credible interval is wider for SCM, due to the heteogeneity of comparing treated regions with counterfactuals which a are close in geographical terms but nevertheless are different in other socio-economic aspects. When comparing regions that are geographically contiguous using SR), heterogeneity of counterfactuals is reduced, and thus the amplitude of the credible intervals diminishes, but the conditional differences between treated regions and counterfactuals tends to be less pronounced than those obtained with SCM.

The most conclusive evidence is obtained for poverty and women empowerment: the results show that with a 95% probability microfinance was useful both for reducing poverty at regional level and encouraging women-empowerment at household level. In the case of unemployment and informality, the evidence of spatial treatment effects is weaker:

- There is strong evidence of microfinance effects on poverty reduction, as the Bayesian 95% credible intervals for the poverty SATE in general does not include zero, particulary when comparing treated regions with their closest matches in terms of geographical distance (i.e., when using SCM and SRM techniques). See Table 2 and Figure 3.
- A similar result is obtained for women empowerment: the percentage of female-headed

[4] During the estimation of BS-PSM, a uniform prior was used for the spatial correlation coefficient ρ, $\pi(\rho) \sim \mathcal{U}(0,1)$, assuming that the existence of financial services in a municipality should increase the chances of having financial services in neighboring municipalities, i.e. a positive spatial correlation of financial access was assumed a priori. For each outcome $\mathbf{O}$, chains with 6000 iterations were simulated and a burn-in of 1000 iterations was chosen to discard the non-stationary part of the chain. Some evidence of autocorrelation was found on the simulated chains. Thinning was applied to eliminate this correlation, but the results between the thinned and the unthinned chains were not extremely different; thus, the estimates of Table 2 are based on the unthinned chains, as nothing advantageous or necessary in thinning was found *per se*; see Link and Eaton (2012).

Table 1: Observed average statistics

Variable	Threshold†	Municipalities with access	Municipalities without access	Observed difference
Poverty (UBN)*	$\mathcal{Q}_0$	60.63	79.49	-18.87
	$\mathcal{Q}_1$	58.12	77.89	-19.87
	$\mathcal{Q}_2$	56.39	76.21	-19.82
	$\mathcal{Q}_3$	55.08	74.42	-19.33
Subjective monetary poverty*	$\mathcal{Q}_0$	57.35	70.96	-13.61
	$\mathcal{Q}_1$	58.42	64.68	-6.258
	$\mathcal{Q}_2$	58.16	63.95	-5.787
	$\mathcal{Q}_3$	59.01	62.29	-3.278
Informality*	$\mathcal{Q}_0$	14.48	9.324	5.155
	$\mathcal{Q}_1$	15.76	8.948	6.814
	$\mathcal{Q}_2$	15.47	10.45	5.018
	$\mathcal{Q}_3$	15.67	11.17	4.501
Unemployment*	$\mathcal{Q}_0$	0.855	0.872	-0.017
	$\mathcal{Q}_1$	0.899	0.842	0.057
	$\mathcal{Q}_2$	0.938	0.833	0.105
	$\mathcal{Q}_3$	0.986	0.831	0.154
Female-headed households**	$\mathcal{Q}_0$	25.21	23.1	2.107
	$\mathcal{Q}_1$	25.62	23.2	2.419
	$\mathcal{Q}_2$	25.97	23.35	2.621
	$\mathcal{Q}_3$	27.01	23.36	3.658

(†) $\mathcal{Q}_0$: $\aleph_i > 0$; $\mathcal{Q}_1$, $\mathcal{Q}_2$, $\mathcal{Q}_3$: three first quintiles of the distribution of $\aleph_i$, respectively
(*) Percentage of the population in a municipality
(**) Percentage of households

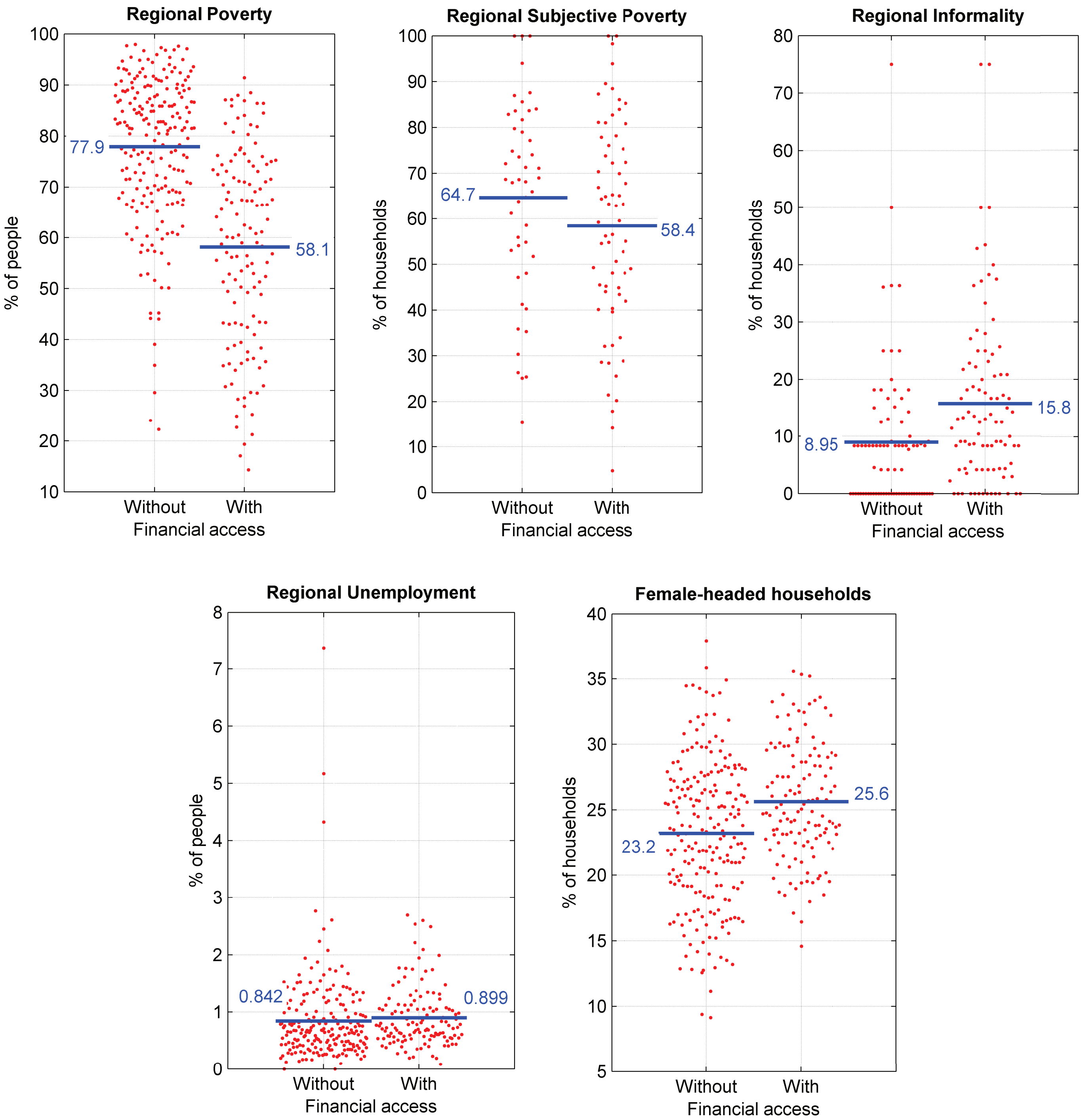

Figure 2: Observed differences at municipality level. Informality is based on survey data and thus lacks of complete information for all the municipalities in Bolivia.

households is on average higher in municipalities where there exist access to microfinance, even after controlling for the similarities between municipalities and the spatial distance between these municipalities: the 95% credible interval of the SATE for women-empowerment is always above zero for all treatment levels $\mathcal{Q}_0$ to $\mathcal{Q}_4$ when using SCM and SRM. See Table 5 and Figure 6.

- The evidence on informality suggests that informal activities in municipalities with microfinance access is on average higher only with low levels of microfinance operations ($\mathcal{Q}_0$, $\mathcal{Q}_1$) as when the intensity of microfinance operations increases to $\mathcal{Q}_2$ and $\mathcal{Q}_3$ the credible interval of the SATE starts crossing zero (Figure 4).
- Finally, in the case of unemployment, the credible intervals of the SATE tend to cross the zero bound a lot (Figure 5) and the Bayesian point estimates of the ATE are close to zero (Table 4), suggesting that there are not important differences in unemployment between municipalities with and without access to microfinance.

In terms of post-estimation statistics (Table 6), the value of Efron's pseudo-R^2 close to 50% suggest an acceptable model fit for the spatial probit models; the spatial correlation is higher for the spatial error models—suggesting that this is the appropriate specification to capture the spatial effects of financial access at municipality level in Bolivia— and the balancing tests in general point to the non-rejection of the null of balanced control covariates; the evidence of compliance with the balancing property is weaker for the variables estimated with survey data (subjective poverty and informality), showing the importance of using complete rich data sets —as census data— to properly evaluate regional effects.

4 Discussion

A Bayesian Spatial-Propensity Score Matching estimator was proposed to evaluate regional treatment effects. This estimator was used to evaluate the overall effects of microfinance on poverty, informality, women empowerment and unemployment at municipality level in Bolivia.
As other studies that found that microfinance contributes to poverty reduction—e.g. Wright (2000), Morduch and Haley (2002) or Khandker (2005)—, a positive impact on poverty reduction at *municipality* level was found with the BS-PSM estimator for Bolivia. In terms of unemployment, the evidence of the impact of microfinance on this variable suggests that there are not important differences in unemployment between municipalities with and without access to microfinance. The heterogeneity of the labor market in Bolivia may be one of the causes of the lack of an observed regional effect on unemployment, thus a measure of the quality of jobs is needed to complement the idea of simply having a job (possibly informal), as underemployment and self-employment are more relevant issues than unemployment in Bolivia.
The most interesting and conclusive results are those for women-empowerment, as the Bayesian SATE estimator showed strong evidence of female-empowerment through decision making at household level in municipalities with microfinance access. This is interesting as microfinance institutions tend to believe that women are more responsible and better money managers than men; moreover, lending to women has been one of the main objectives and flagships of microfinance in Bolivia.
From a methodological point of view, the Bayesian spatial-propensity score matching estimator seems to be an interesting improvement over traditional matching estimators. BS-PSM allows taking into account spatial factors during the matching, which are important if the distance to financial institutions is a constraint to financial inclusion and affects regional growth. Moreover, the full density of the spatial average treatment effect can be estimated with the the BS-PSM algorithm, allowing to perform a rigorous inferential analysis based on credible intervals and not only on point estimates of the average treatment effects. Both improvements allow a proper quasi-experimental impact evaluation of the overall effects of a treatment at regional level.

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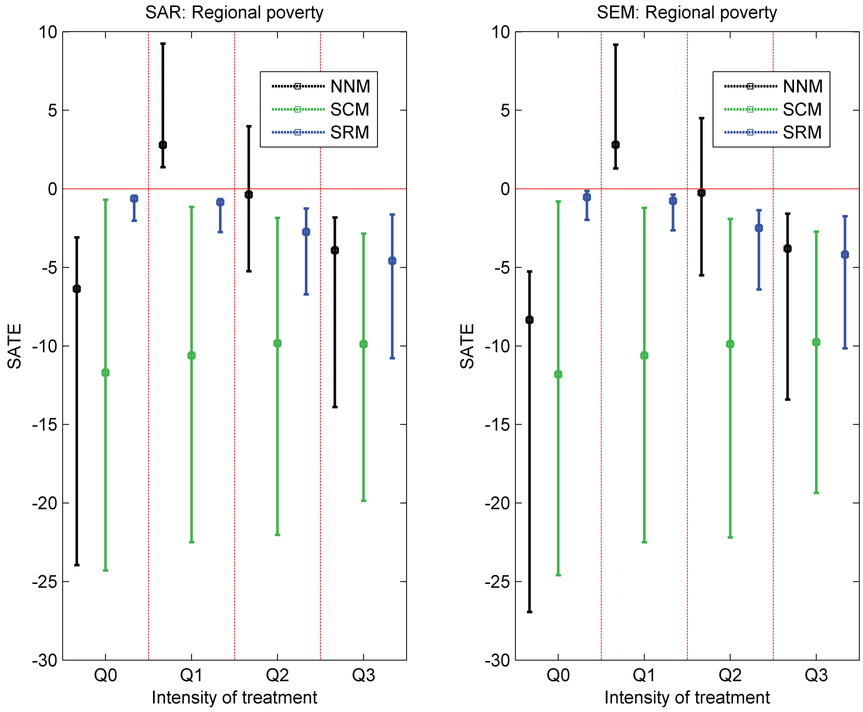

Figure 3: Spatial Average Treatment Effects: Poverty (UBN)

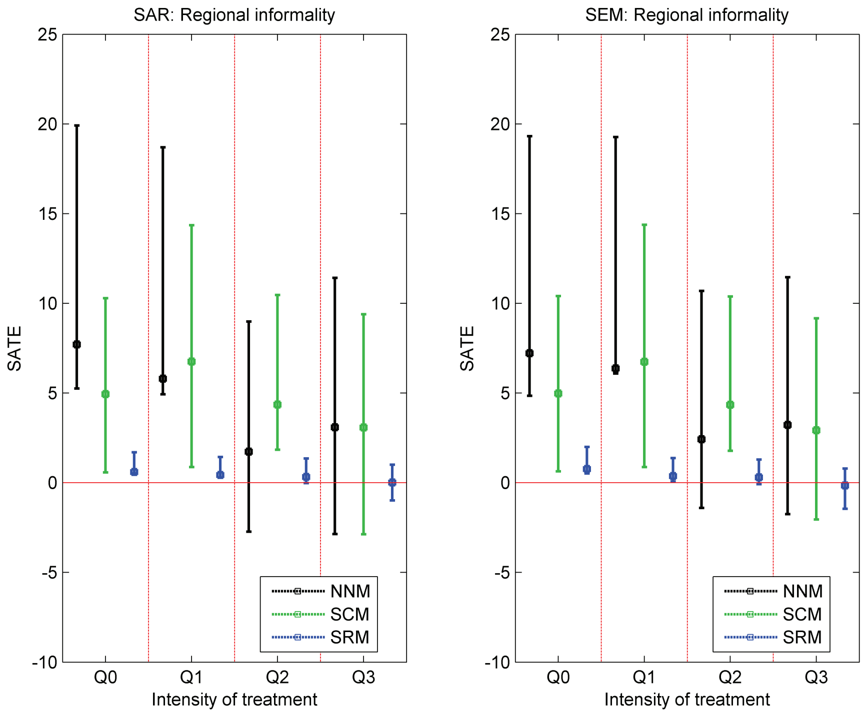

Figure 4: Spatial Average Treatment Effects: Informality

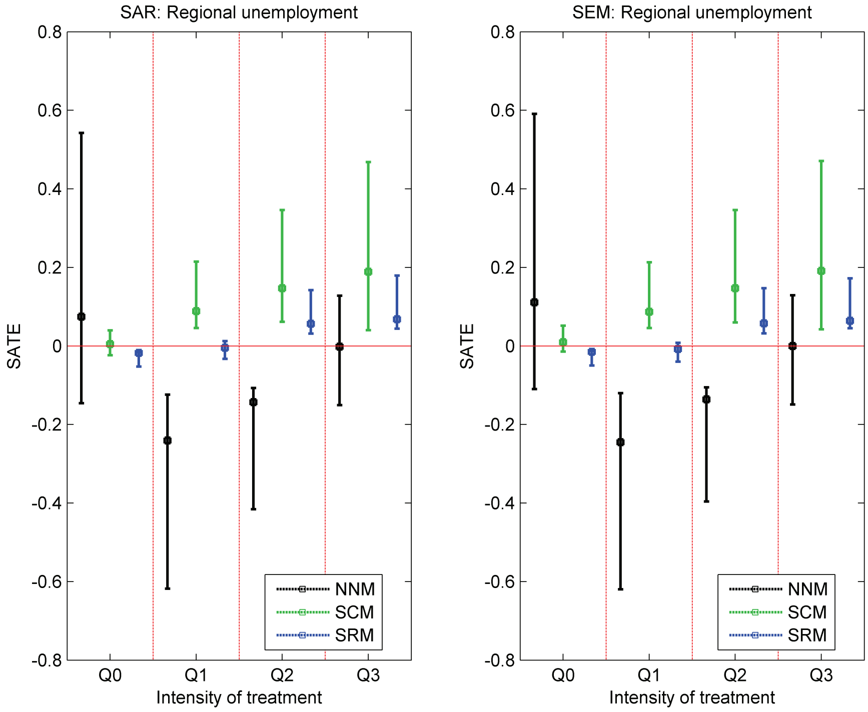

Figure 5: Spatial Average Treatment Effects: Unemployment

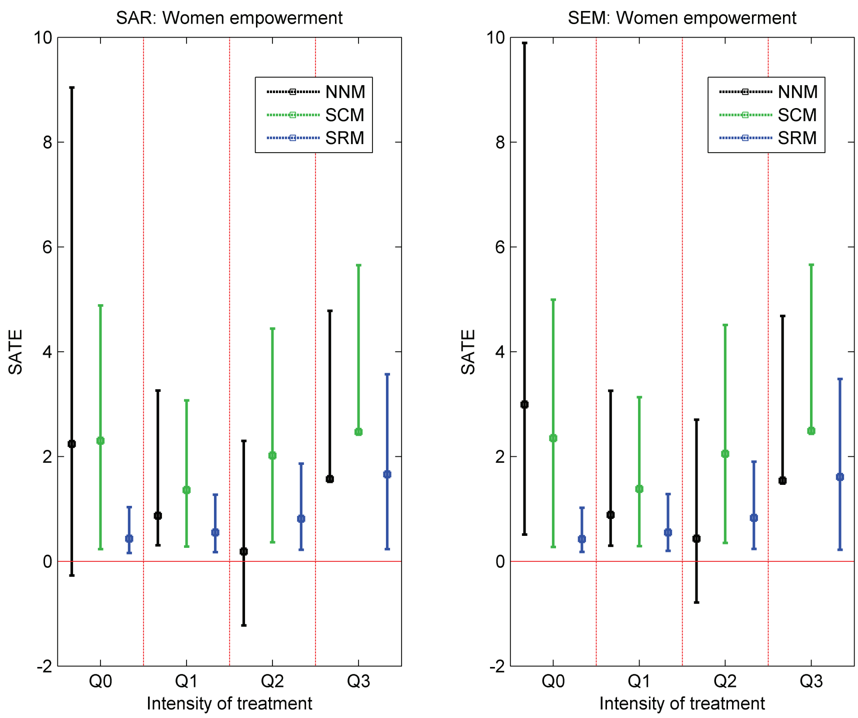

Figure 6: Spatial Average Treatment Effects: Female-headed households

Table 2: Regional effects of microfinance on poverty*

Treatment Intensity	SAR NNM	SAR SCM	SAR SRM	SEM NNM	SEM SCM	SEM SRM
SATE ($\hat{\vartheta}_u$)						
$\mathcal{Q}_0$	-6.36	-11.7	-0.616	-8.34	-11.8	-0.536
	(-17.6, 3.26)	(-12.6, -11)	(-1.42, 0.158)	(-18.6, 3.08)	(-12.8, -11)	(-1.44, 0.395)
$\mathcal{Q}_1$	2.8	-10.6	-0.842	2.81	-10.6	-0.767
	(-1.42, 6.44)	(-11.9, -9.44)	(-1.91, 0.186)	(-1.52, 6.36)	(-11.9, -9.38)	(-1.88, 0.394)
$\mathcal{Q}_2$	-0.374	-9.83	-2.74	-0.247	-9.89	-2.5
	(-4.88, 4.36)	(-12.2, -7.98)	(-3.98, -1.49)	(-5.26, 4.74)	(-12.3, -7.97)	(-3.91, -1.13)
$\mathcal{Q}_3$	-3.91	-9.89	-4.58	-3.81	-9.76	-4.19
	(-9.98, 2.08)	(-13.1, 7.04)	(-6.21, -2.95)	(-9.6, 2.23)	(-13.1, -7.03)	(-5.97, -2.44)

(*) Between brackets below each point estimate: 95% Bayesian credible interval
SAR: Spatial autoregressive model
SEM: Spatial error model
NNM: Nearest-neighbors matching
SCM: Spatial caliper matching
SRM: Spatial radial matching

Table 3: Regional effects of microfinance on informality*

Treatment Intensity	SAR NNM	SAR SCM	SAR SRM	SEM NNM	SEM SCM	SEM SRM
SATE ($\hat{\vartheta}_u$)						
$\mathcal{Q}_0$	7.71	4.94	0.596	7.22	4.98	0.77
	(2.46, 12.2)	(4.37, 5.35)	(0.0747, 1.1)	(2.38, 12.1)	(4.34, 5.42)	(0.25, 1.23)
$\mathcal{Q}_1$	5.8	6.75	0.435	6.37	6.74	0.378
	(-0.875, 12.9)	(5.88, 7.6)	(-0.148, 0.996)	(-0.284, 12.9)	(5.87, 7.64)	(-0.318, 0.993)
$\mathcal{Q}_2$	1.73	4.36	0.322	2.43	4.35	0.3
	(-4.46, 7.25)	(2.52, 6.1)	(-0.338, 1.03)	(-3.83, 8.26)	(2.57, 6.03)	(-0.382, 0.99)
$\mathcal{Q}_3$	3.09	3.08	0.0174	3.22	2.92	-0.151
	(-5.95, 8.33)	(-0.39, 6.31)	(-1.01, 0.982)	(-4.97, 8.24)	(-0.422, 6.24)	(-1.3, 0.936)

(*) Between brackets below each point estimate: 95% Bayesian credible interval
SAR: Spatial autoregressive model
SEM: Spatial error model
NNM: Nearest-neighbors matching
SCM: Spatial caliper matching
SRM: Spatial radial matching

Table 4: Regional effects of microfinance on unemployment*

Treatment Intensity	SAR			SEM		
	NNM	SCM	SRM	NNM	SCM	SRM
SATE ($\hat{\vartheta}_u$)						
$\mathcal{Q}_0$	0.074	0.005	-0.018	0.111	0.009	-0.015
	(-0.22, 0.468)	(-0.029, 0.035)	(-0.035, -0.001)	(-0.221, 0.48)	(-0.024, 0.042)	(-0.035, 0.003)
$\mathcal{Q}_1$	-0.241	0.089	-0.005	-0.245	0.087	-0.008
	(-0.377, 0.117)	(0.043, 0.126)	(-0.028, 0.017)	(-0.375, -0.125)	(0.041, 0.126)	(-0.032, 0.016)
$\mathcal{Q}_2$	-0.143	0.147	0.056	-0.136	0.147	0.058
	(-0.273, -0.036)	(0.086, 0.199)	(0.025, 0.086)	(-0.26, 0.031)	(0.088, 0.199)	(0.026, 0.089)
$\mathcal{Q}_3$	-0.002	0.189	0.068	0	0.191	0.064
	(-0.149, 0.13)	(0.108, 0.279)	(0.024, 0.111)	(-0.149, 0.129)	(0.109, 0.28)	(0.019, 0.108)

(*) Between brackets below each point estimate: 95% Bayesian credible interval
SAR: Spatial autoregressive model
SEM: Spatial error model
NNM: Nearest-neighbors matching
SCM: Spatial caliper matching
SRM: Spatial radial matching

Table 5: Regional effects of microfinance on women empowerment*

Treatment Intensity	SAR			SEM		
	NNM	SCM	SRM	NNM	SCM	SRM
SATE ($\hat{\vartheta}_u$)						
$\mathcal{Q}_0$	2.24	2.3	0.43	2.99	2.35	0.423
	(-2.51, 6.8)	(2.07, 2.58)	(0.274, 0.601)	(-2.48, 6.9)	(2.08, 2.64)	(0.246, 0.598)
$\mathcal{Q}_1$	0.868	1.36	0.549	0.884	1.38	0.55
	(-0.564, 2.39)	(1.08, 1.71)	(0.374, 0.72)	(-0.587, 2.37)	(1.09, 1.75)	(0.351, 0.733)
$\mathcal{Q}_2$	0.186	2.02	0.813	0.432	2.05	0.83
	(1.41, 2.11)	(1.66, 2.42)	(0.593, 1.05)	(-1.22, 2.27)	(1.7, 2.46)	(0.595, 1.07)
$\mathcal{Q}_3$	1.57	2.47	1.66	1.54	2.49	1.61
	(-0.0455, 3.21)	(1.78, 3.18)	(1.43, 1.91)	(-0.0569, 3.14)	(1.81, 3.17)	(1.39, 1.87)

(*) Between brackets below each point estimate: 95% Bayesian credible interval
SAR: Spatial autoregressive model
SEM: Spatial error model
NNM: Nearest-neighbors matching
SCM: Spatial caliper matching
SRM: Spatial radial matching

Table 6: BS-PSM post-estimation statistics

	Poverty (UBN)		Subjective Poverty		Unemployment		Informality		Empowerment	
	SAR	SEM	SAR	SEM	SAR	SEM	SAR	SEM	SAR	SEM
Efron's pseudo R^2										
R^2	52.03	52.26	46.96	47.61	51.73	51.66	46.31	45.56	51.99	52.02
Spatial Correlation†										
ρ	0.019	0.155	0.081	0.261	0.019	0.162	0.048	0.462	0.020	0.159
ρ_L	0.000	0.012	0.005	0.015	0.000	0.016	0.002	0.053	0.001	0.012
ρ_U	0.069	0.365	0.321	0.837	0.077	0.418	0.160	0.880	0.069	0.391
Balancing tests‡										
$\mathbf{x}_1$	0.4787	0.4691	0.1372	0.0860	0.4901	0.4986	0.2468	0.2424	0.4783	0.4719
$\mathbf{x}_2$	0.1238	0.1167	0.0015	0.0013	0.1250	0.1254	0.0217	0.0300	0.1261	0.1148
$\mathbf{x}_3$	0.3606	0.3434	0.0554	0.0621	0.3856	0.3779	0.1373	0.2001	0.3438	0.3607
$\mathbf{x}_4$	0.0862	0.0876	0.0653	0.0578	0.1024	0.1021	0.0348	0.0531	0.0904	0.1010
$\mathbf{x}_5$	0.3819	0.3685	0.0533	0.0678	0.4015	0.3939	0.1000	0.1183	0.3769	0.3861
$\mathbf{x}_6$	0.0470	0.0438	0.0123	0.0102	0.0446	0.0463	0.0184	0.0189	0.0443	0.0473
$\mathbf{x}_7$	0.0474	0.0487	0.0926	0.0906	0.0565	0.0624	0.1591	0.2074	0.0521	0.0550
$\mathbf{x}_8$	0.1054	0.1066	0.0508	0.0571	0.1088	0.1155	0.0200	0.0278	0.1092	0.1027
$\mathbf{x}_9$	0.0627	0.0671	0.0428	0.0390	0.0697	0.0783	0.0156	0.0261	0.0605	0.0759
*Spatial Probit estimates**										
$\mathbf{x}_0$	-33.730	-33.954	-45.797	-50.875	-33.488	-34.542	-29.941	-31.815	-33.183	-34.429
$\mathbf{x}_1$	0.6367	0.6644	0.6027	0.8313	0.6227	0.5935	0.4045	0.3816	0.6307	0.6475
$\mathbf{x}_2$	0.3266	0.3277	0.3995	0.4428	0.3240	0.3318	0.2868	0.3090	0.3213	0.3307
$\mathbf{x}_3$	-0.019	-0.020	-0.011	-0.009	-0.019	-0.020	-0.025	-0.031	-0.019	-0.019
$\mathbf{x}_4$	-0.028	-0.027	-0.037	-0.047	-0.027	-0.027	-0.023	-0.024	-0.027	-0.027
$\mathbf{x}_5$	0.0002	0.0002	0.0058	0.0100	0.0004	-0.0002	0.0043	0.0044	0.0006	0.0001
$\mathbf{x}_6$	0.2780	0.2213	0.4260	0.4786	0.2258	0.1551	-0.5615	-1.0353	0.2607	0.2479
$\mathbf{x}_7$	0.0085	0.0095	0.0068	0.0094	0.0088	0.0097	0.0054	0.0024	0.0089	0.0099
$\mathbf{x}_8$	0.2264	0.2303	0.3422	0.3680	0.2252	0.2400	0.2262	0.2501	0.2231	0.2342
$\mathbf{x}_9$	0.0279	0.0279	0.0694	0.0752	0.0276	0.0301	0.0314	0.0367	0.0268	0.0288

(†) ρ: Bayesian point estimate; ρ_L, ρ_U: lower and upper limit of a 95% Bayesian credible interval
(‡) Bayesian p-values for the null of balanced variable
(*) Bayesian point estimates. The term $\mathbf{x}_0$ is the constant in the spatial models

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