Is microfinance truly useless for poverty reduction and women empowerment? A bayesian spatial-propensity score matching evaluation in Bolivia

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Abstract

Banerjee et al. (2015) presented the results of six randomized evaluations that led them to conclude that micro-credit does not have a transformative impact on poverty and that little evidence of substantial effects on women’s empowerment exist. We argue that even if no effects of micro-finance exist at the household/individual level, there still may be observable effects at the regional level due to the wider impacts of microfinance. A Bayesian Spatial-Propensity Score Matching estimator is proposed to measure these regional (spatial) treatment effects. The regional effects of microfinance in Bolivia were tested with this estimator, using census and household survey data. The results – conditional on the assumptions of the study– showed that microfinance was useful for poverty reduction and women’s-empowerment at the municipal level in Bolivia, thus suggesting that microfinance can be used to promote socio-economic development at the regional level.

JEL codes: C11, C31, G21

Keywords: Microfinance, spillover effects, Bayesian methods, spatial statistics, matching

SSRN-ERN subjects: Bayesian analysis; microfinance; cross-sectional, spatial, treatment effect models estimators

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List of abbreviations

ATE Average Treatment Effect
BS-PSM Bayesian Spatial Propensity Score Matching
ECLAC Economic Commission for Latin America and the Caribbean
GIS Geographic Information System
GUM General Unrestricted Model
MCMC Markov Chain Monte Carlo
NGO Non-Governmental Organization
J-PAL Abdul Latif Jameel Poverty Action Lab
SATE Spatial Average Treatment Effect
SEM Spatial Error Model
UBN Unsatisfied Basic Needs
Executive summary

The impact of microcredit is a subject of controversy: proponents of microfinance state that microfinance reduces poverty through higher employment and higher incomes, which in turn improves health and education. Detractors of the microfinance model disbelieve in the poverty-reduction role of microfinance and further suggest that microfinance is damaging the possibility of development due to crowding out effects. Recently, Banerjee et al. (2015) presented more rigorous evidence based on six randomized evaluations around the world; the findings of Banerjee et al. (2015) led them to conclude that micro-credit does not have a transformative impact on poverty; also, little evidence of substantial effects on women’s empowerment was found in these studies. Even if no effects of micro-finance exist at household/individual level—as suggested by the findings of Banerjee et al. (2015)—there still may be observable regional effects due to the externalities caused by the wider impacts of microfinance. A Bayesian Spatial-Propensity Score Matching (BS-PSM) estimator was proposed to measure these regional effects. The BS-PSM estimator was used to evaluate the regional effects of microfinance in Bolivia. The results—conditional on the assumptions of the study—showed that microfinance was useful for poverty reduction and women’s empowerment at the municipal level in Bolivia, with the possible cost of increasing informality. These findings suggest that microfinance can be used to enhance socio-economic development beyond the household or individual level if policies of financial expansion at the regional level take into account the potential spillover effects of microfinance.
I. Introduction

Microfinance is the provision of small-scale financial services to low-income clients who lack access to traditional banking services (Karlan and Goldberg, 2007). The impact of microcredit is a subject of controversy: proponents of microfinance—as the Nobel Laureate Muhammad Yunus or World Bank's President Jim Yong Kim—state that microfinance reduces poverty through higher employment and higher incomes, which in turn improves health and education. Detractors of the microfinance model disbelieve in the poverty-reduction role of microfinance and further suggest that microfinance is damaging the possibility of development due to crowding out effects (see, e.g., Bateman, 2010).

Much of the literature on the impact of microcredit is anecdotal and qualitative; see Weiss and Montgomery (2005) for a review. Recently, Banerjee et al. (2015) presented more rigorous results based on six randomized evaluations around the world; the findings of Banerjee et al. (2015) led them to conclude that microcredit does not have a transformative impact on poverty, in the sense of lifting people or communities out of poverty, due to a lack of clear/suggestive evidence of substantial improvements in living standards; also, little evidence of effects on women's empowerment was found in the randomized evaluations, as four of the studies evaluated the effects on female decision-making power and/or independence within the household, and three found no effects.

Even if no effects of microfinance exist at the household/individual level—as suggested by the findings of Banerjee et al. (2015)—there still may be observable regional effects due to the externalities caused by the wider impacts of microfinance. These overall regional effects arise when the impact of microfinance spreads out beyond target clients and towards other economic agents within the same geographical unit and/or neighboring units, due to the economic interaction between the recipients of microfinance and the non-participant population.

A Bayesian Spatial-Propensity Score Matching (BS-PSM) estimator is proposed to measure these regional effects. The BS-PSM estimator was used to evaluate the regional effects of microfinance in Bolivia. The findings showed that microfinance was useful for poverty reduction and women's empowerment at the municipal level in Bolivia, with the possible cost of increasing informality.

Section 2 offers a brief literature review on the wider impacts of microfinance. Section 3 shows the BS-PSM estimator of Spatial Average Treatment Effects (SATE). Section 4 presents an application for the Bolivian case. Section 5 discusses the results and concludes. Appendix I at the end of the paper shows the mathematical details of BS-PSM estimation. Appendix II runs a falsification test to evaluate the BS-PSM algorithm and Appendix III compares an estimation with and without spatial information. The MATLAB code to replicate the results is available upon request.

II. Wider impacts of microfinance

The analysis about the impacts of microfinance tends to be exclusively focused on the direct impact on microfinance clients (Chowdhury et al., 2004). In contrast, the wider impacts of microfinance affect non-client beneficiaries and do not operate primarily at the individual or household level (Zohir and Matin, 2004). These wider effects are commonly measured through spatial models of the type
described in *inter alia* Anselin (1988), Arbia (2010), Anselin and Florax (2011) or Griffith and Paelinck (2011), as at the regional level the probability of having access to microfinance is influenced by the proximity to other regions with financing facilities, and the dynamics of one local economy influences neighboring local economies, through trade linkages and market relationships—such as demand linkages and interregional mobility of production factors—with the level of influence spatially bounded by the distance between regions (Capello, 2009).

The wider impacts of microfinance on poverty arise due to positive income spillovers from microfinance beneficiaries to other members of a community where microfinance is offered (Glennerster and Takavarasha, 2013); negative spillovers may arise if microfinance institutions give priority to weak and generally short-lived informal enterprises over riskier but longer-term enterprises (Bateman, 2013); displacement effects arise if these informal microenterprises and self-employment ventures crowd out the operations of formal and sustainable small-medium enterprises with prospects of technological upgrading, which are widely seen as the source of formal employment and growth in developing and transition countries—see Bateman and Chang (2009) or Bateman (2010). Even more, for Bateman (2013), microfinance is a very powerful ‘anti-development’ intervention that locally embeds poverty, deprivation, inequality and backwardness, because of the progressive de-industrialization and informalization of the local enterprise sector and local economy, which destroys the capacity for raising productivity and the possibility of securing sustainable development, growth and long-term poverty reduction.

In terms of women’s empowerment, Glennerster and Takavarasha (2013) provide a nice example of the potential spillover effects of gender-oriented microfinance: positive effects within a treatment group (a community) can arise if women who take up microfinance will start businesses and employ their neighbors to help them, thereby sharing some of their increased income with their neighbors. Thus even women who do not borrow may benefit from being in a community where microfinance is offered. Negative spillovers arise if women with existing businesses are harmed by the arrival of microfinance because they will face more competition from new borrowers who start businesses that cater to the local community and offer similar products, thus affecting those in the community who do not take up microfinance.

Empirical studies about the wider impacts of microfinance are *inter alia* Mosley (2003), Mosley and Rock (2004), Khalily (2004), Wright and Copestake (2004), Chowdhury and Bhuinya (2004), Johnson (2004), Velasco and Marconi (2004) or McIntosh (2008). In terms of positive spillovers, these studies found that microfinance has the potential to stabilize income at the community level (Mosley, 2003), generate derived demand and other economic spillovers through the labor market (Mosley and Rock, 2004) and assist microenterprises in maintaining an increased level of output and investment during recessions (Velasco and Marconi, 2004). In terms of negative spillovers, Velasco and Marconi (2004) found that the entry of consumer credit houses into microcredit can destabilize loan discipline and the entire bottom end of the financial system.

Studies that analyzed the impact of microfinance in Bolivia are *inter alia* McKnelly and Dunford (1999), Navajas et al. (2000), Mosley (2001), Brett (2006), Velasco and Marconi (2004) and Gonzales (2010). McKnelly and Dunford (1999) ran a longitudinal study which compared to the baseline for nutritional data, with a control group of communities who would be offered same program two years later. No
evidence of improvements in household food security or nutritional status of client’s children relative to the control group was found by McKnelly and Dunford (1999). Navajas et al. (2000) compared poverty in income terms of a sample of the borrowers of five microfinance organizations with the poverty of all households in La Paz, a major city of Bolivia. Navajas et al. (2000) found that microfinance organizations tended to serve not the poorest but rather those near the poverty line. Using data of borrowers of microfinance in Bolivia and a control sample with a before-after methodology, Mosley (2001) found that the growth of incomes and assets of borrowers always exceeds that of control group, but no evidence of this effect was found for the extreme poor. More recently, in his suggestive ethnographic article “We Sacrifice and Eat Less: The Structural Complexities of Microfinance Participation”, Brett (2006) found that, having borrowed money from a microfinance organization to start a small business, many women in El Alto, Bolivia are unable to generate sufficient income to repay their loans and so must draw upon household resources. Finally, Gonzales (2010) analyzed the regional impacts of credit for economic development and found that on average municipalities with access to financial services have better human development indicators.

Even if Velasco and Marconi (2004) or Gonzales (2010) analyzed the regional impacts of microfinance access in Bolivia before, due to the recent availability of the 2012 Census of Bolivia, there is new data to perform a more accurate assessment about the regional impact of financial access in this country. Also, previous studies did not perform a rigorous impact evaluation, and as BS-PSM is a spatial quasi-experimental design, it is a methodological improvement over past studies.

### III. Bayesian spatial-propensity score matching and spatial average treatment effects

This section presents an estimator to measure regional treatment effects. Let \( t \) be a \( n \times 1 \) vector of 0,1 binary values for the absence/presence of a treatment in a region \( i = 1, \ldots, n \), \( W \) a \( n \times n \) row-stochastic proximity matrix between regions, \( X \) a \( n \times p \) matrix of \( p \)-control covariates, \( y \) a \( n \times 1 \) vector with data of a regional outcome, and \( \Theta \) a vector of parameters. A Spatial Average Treatment Effect (SATE) can be defined as a random variable \( \vartheta \) in terms of a matching function \( M(\cdot) \) of \( t, W, X, y, \Theta \),

\[
\text{SATE} := \vartheta = M(t, W, X, y, \Theta),
\]

\[
= E_{W,\Theta \{ y_i | t_i = 1, X_{1i} = x_1, \ldots, X_{pi} = x_p \} - \{ y_i | t_i = 0, X_{1i} = x_1, \ldots, X_{pi} = x_p \}}.
\]

A density estimation of the SATE can be obtained with

\[
\hat{\vartheta} = \{ M(t, W, X, y, \Theta^{(g)}) \}_{g=1}^G
\]

based on \( g \)-draws of a (Bayesian) spatial probit model, using a spatial matching function to estimate the average *regional* differences between treated and untreated groups, conditional on observable
characteristics. For a dataset \( \mathcal{D} \), optimal point estimators and \( \gamma \)-credible intervals for the SATE can be calculated from \( \theta \) with \( \mathbb{E}(\theta | \mathcal{D}) \) and

\[
\int_{\mathcal{C}_{\theta, \gamma}} \pi(\theta | \mathcal{D}) d\theta,
\]

using a Markov Chain Monte Carlo (MCMC) sampler; see the Appendix for details.

Compared with variance adjustment methods,\(^1\) the Bayesian approach guarantees positive standard errors, is more reliable in small samples and can be readily employed to estimate the complete posterior distribution of the SATE, thus naturally incorporating uncertainties into causal inference. Hoshino (2008), McCandless et al. (2009), Chib and Greenberg (2010), An (2010), Kaplan and Chen (2012), Alvarez and Levin (2014), Zigler and Dominici (2014) or Zigler (2014) proposed Bayesian alternatives to frequentist propensity score matching, and spatial propensity score matching was used by Chagas et al (2011),\(^2\) but, to our knowledge, a spatial propensity score matching estimator was never constructed from a Bayesian perspective before.\(^3\)

### IV. Application: Regional effects of microfinance in Bolivia

This section shows an application of BS-PSM for the evaluation of the regional effects of microfinance in Bolivia. Bolivia is an interesting case study due to its paradigmatic microfinance history: the first initiatives to offer small credits in Bolivia were carried out by NGOs back in the 1980s. During the early 1990s, NGOs were transformed into regulated microfinance institutions. The rapid growth and high rates of profit of these institutions attracted more players into the market and Bolivia eventually became one of the best environments for microfinance around the world: Bolivia was listed several times as the runner-up top performer worldwide, just behind Peru, in the Global Microscope on the Microfinance Business Environment sponsored by the Inter-American Development Bank—see Economist Intelligence Unit (2010) and Economist Intelligence Unit (2011).

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\(^1\) 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, even if bootstrap might look like a natural candidate to estimate the cumulative distribution function of ATE due to consistency theorems, Abadie and Imbens (2008) also showed that bootstrap is not valid for calculating the standard errors of matching estimators, even in the simple case with a single continuous covariate and nearest neighbor matching.

\(^2\) McIntosh (2008) also used a classical (frequentist) spatial matching estimator to evaluate two innovations in Ugandan microfinance, in order to measure how regional shocks such as an Ebola outbreak and a contentious presidential election altered outcomes differentially across regions. By correcting for this spatial heterogeneity, McIntosh (2008) found that a program that increased borrowers’ control over the terms of their loans improved outcomes, while the results of a program that bundled health insurance into the lending contract were mixed.

\(^3\) Searching in Google Scholar, we found 30200 results for “Propensity Score Matching” 31 for “Spatial Propensity Score Matching” and 12 for “Bayesian Propensity Score Matching”, but no results were obtained when searching for “Spatial Bayesian Propensity Score Matching” (except the one of our paper). See Efron (2013) for an informal introduction to Bayesian methods.
During 1992-2012, there was a remarkable growth of microcredit in Bolivia: in 1991 the borrowers served by agencies specializing in microfinance reached 19% of all clients in the lending market, in 2012 this percentage increase to 65% of all clients in the lending market.

The expansion of microcredit led to the development of lending technologies that were adapted to the needs of micro-borrowers: solidarity groups, individual credits and communal banks. In solidarity groups, conventional guarantees are replaced by a shared security, thus allowing credit access for poor populations. Individual credits are aimed to transform micro-enterprises into small-medium businesses, and the joint-security technology of communal banks focuses on introducing financial services and education in women’s groups.

Due to the advances in lending technology, microfinance is one of the most important financial activities in Bolivia: on September 30, 2014, the gross portfolio of specialized Microcredit Entities (MCEs) was 33% of the total portfolio of financial intermediation in Bolivia (see the graph to the left).

Of the total amount of loans allocated by MCEs, 59% were allocated to men and 41% to women. Both in terms of portfolio and number of clients, microcredit is concentrated in the major departments of Bolivia: La Paz, Santa Cruz and Cochabamba.

Using census and household survey data, BS-PSM was used to estimate the conditional differences between municipalities of Bolivia with and without access to microfinance. The estimated probabilities of financial access, given the spatial distance $W$ and the observed covariates $X$, were used to match municipalities with similar characteristics. The difference between 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).

During the estimation of BS-PSM, a uniform prior was used for the spatial correlation coefficient $\rho$, $\pi(\rho)\sim U(0,1)$, 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, chains with 1100 iterations were simulated and a burn-in of 100 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 un-thinned chains were not extremely different; thus, the estimates of the SATE are based on the un-thinned chains, as nothing advantageous or necessary in thinning was found per se; see Link and Eaton (2012). Post-estimation tests and statistics were calculated to evaluate the spatial models, using the pseudo-R2 statistic proposed by Efron (1978) and the Bayesian version of the Smith and Todd (2005) balancing property test proposed by Gonzales (2015).
Data and variables

Census information at the municipal level was used to estimate the effects of microfinance in Bolivia because census data at the locality/household level is not available for the public due to the data disclosure policy of the Bolivian government. Data on microfinance was gathered from the Supervisory Authority of the Financial System in Bolivia. Household survey data was used to approximate a measure of informality.

Access to microfinance was measured with the scaled number of microfinance operations in a municipality of Bolivia. Let \( \mathcal{K}_i \) be the number of microfinance operations in a municipality \( i = 1, \ldots, n \) of Bolivia, divided by the economically active population of this municipality. The binary variable \( t_i \) in the vector of financial access \( \mathbf{t} \) is equal to,

\[
t_i = \begin{cases} 
1 & \text{if } \mathcal{K}_i \geq Q \\
0 & \text{if } \mathcal{K}_i < Q
\end{cases}
\]

for a threshold \( Q \in \mathbb{R}^+ \). The centiles of the number of microfinance operations in Bolivia were used as the thresholds \( Q \). This quasi-continuous estimation of the SATE allows measuring the effects of differential treatment intensities (Warren et al., 2007), i.e. the differences in the impact on poverty, women’s empowerment and informality related to the different number of microfinance operations in a municipality. This approach is similar to the dose-response function proposed by Hirano and Imbens (2004).

The 339×9 matrix \( \mathbf{X} \) is organized with 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.
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.

Variables (1) to (8) were calculated with the public information from the 2012 National Census of Population and Households of Bolivia; (9) is based on administrative records. These variables were selected from a large set (a General Unrestricted Model, GUM) using a general-to-specific modeling approach (Campos et al., 2005) in order to satisfy the conditional independence assumption (i.e. after controlling for the covariates in \( \mathbf{X} \), the potential outcomes are independent of treatment status).
The GUM model—i.e. the most general statistical model that can reasonably be postulated initially, given the available sample of data, previous empirical and theoretical research, and any institutional and measurement information available (Hendry and Nielsen, 2007)—originally included several variables from the census data, such as the average years of education of the population, emigration, number of households with a vehicle or the number of own-account workers in the municipality, among other variables.

In terms of outcome variables, poverty was measured with the Unsatisfied Basic Needs (UBN) method, which is a multidimensional measure of poverty that 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). Female empowerment was defined as the proportion of female-headed households in a municipality which are not separated, divorced or widowed. This variable measures women’s empowerment through decision-making at the household level, as women are female household heads even in the presence of a husband or partner in the household; a similar measure of empowerment was used by Yogendrarajah (2013). 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

Proximity matrix between regions

Based on the Geographic Information System (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 between the municipalities of Bolivia. The resulting proximity matrix is a 339 x 339 square matrix W.

---

4 During the modelling stage a trade-off was also encountered between poorly estimated propensity scores —when reducing the number of control covariates—and the potential problem of control covariates connected to the outcomes. The final set of covariates in the spatial probit model were chosen after erasing other variables that were more connected to the outcomes and because further reducing the number of variables below nine covariates dramatically reduces the quality of matching. As UBN poverty is constructed with several variables that are not included as control covariates in the model, the problem of covariates connected to outcomes with this set of control covariates may not be that severe.
Figure 1: Delaunay triangulation and adjacency matrix

Observed differences at the municipal level

Figure 2 shows the observed data of poverty and female-empowerment for the 399 municipalities of Bolivia (each dot is a municipality). In the case of informality, the household survey data does not cover all the municipalities of Bolivia but only 173 municipalities.

The observed data shows that, on average in 2012, the percentage of people living in poverty according to UBN was 79% in municipalities without access to microfinance, and in contrast, the percentage of people living in poverty in municipalities with access to microfinance was on average 61%, thus there was 18 percentage points (pp) less of UBN poverty in municipalities with access to microfinance in Bolivia. In terms of women’s empowerment, the percentage of female-headed households in municipalities with access to microfinance was 25.2% on average, 2.1 pp higher than those municipalities without access to microfinance. Informality was equal to 14.5% in municipalities with microfinance, 5.2 pp higher than those municipalities without microfinance.
Spatial average treatment effects of microfinance in Bolivia

Figures 3, 4, 5 and Tables 1 and 2 show the results of using BS-PSM to estimate the effects of microfinance at the municipal level in Bolivia. Figures 3, 4 and 5 show the probability distribution of the differences in poverty, female empowerment and informality for each centile of microfinance treatment, next to the chains of the Markov Chain Monte Carlo (MCMC) sampler used to estimate these probability distributions. The estimation of the SATE was not computationally feasible when getting close to the 100th centile of treatment, due to close-to-singular-matrix errors. As the units of analysis are municipalities, the data is self-weighted and the estimators of the spatial probit model and the SATE were not weighted.

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

Poverty

Using the UBN measure of poverty there is strong evidence of microfinance effects on poverty reduction at the municipal level in Bolivia: the Bayesian 95% credible intervals for the SATE of poverty do not include zero for any centile $Q$ of microfinance operations (Figure 3, left) and the chains of the MCMC sampler are strongly stationary for each centile (Figure 3, right). Table 1 shows that, on average, municipalities with access to microfinance tend to have around 11pp less of their population living in poverty compared with those municipalities without access to microfinance. This estimated difference in poverty is lower than the observed difference of 18pp, showing that after controlling for other regional and socio-economic characteristics the effect of microfinance on poverty is smaller but still important with a 95% credible interval.
Figure 3: Spatial average treatment effects - poverty

Figure 4: Spatial average treatment effects – women’s empowerment
Figure 5: Spatial average treatment effects – informality

Female empowerment

In the case of women’s empowerment, the estimated 95% credible interval of the SATE was above zero for the different intensities of microfinance access, showing that the percentage of female-headed households was on average higher in municipalities with access to microfinance, even after controlling for the similarities between municipalities and the spatial distance between these municipalities. Again the chains of the MCMC sampler are strongly stationary in each centile (Figure 4, right), showing a good chain convergence.

Interestingly, the number of female-headed households in a municipality tends to increase as the number of regional microfinance operations increases: Table 1 shows that for the centile 25 (corresponding to a small number of microfinance operations) those municipalities with access to microfinance tend to have 1.61pp more female-headed households than those municipalities without access to microfinance; this percentage increases to 2.68pp for the 50th centile (corresponding to a middle level of microfinance operations) and was 2.11pp for the 75th centile (corresponding to a high number of microfinance operations). After a peak in the 60th centile (3.27pp), a reduction of the differences between regions with and without microfinance is observed (Figure 4, left); this change in the trend of the spatial treatment effects suggests a differential impact of microfinance on women’s empowerment, as the magnitude of the effect of microfinance on female empowerment through decision-making at the household level changes as the number of microfinance operations in a region increases.

Informality

The evidence on informality suggests that informal activities in municipalities with microfinance is on average higher only with low and middle levels of microfinance operations (below the 60th centile) as when the intensity of microfinance operations increases above the 60th centile, the credible intervals of the SATE start crossing zero (Figure 5, left) suggesting no
differences in informality when there is a large number of microfinance operations in a region. This result should be nonetheless taken with caution, as it is based on household survey data which does not cover all the municipalities of Bolivia.

Table 1: Spatial average treatment effects of microfinance in Bolivia*

<table>
<thead>
<tr>
<th>Centile 25</th>
<th>Centile 50</th>
<th>Centile 75</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Un-weighted estimates</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Poverty</td>
<td>-11.09 (-12.46, -9.81)</td>
<td>-12.35 (-14.25, -10.82)</td>
</tr>
<tr>
<td>Women’s empowerment</td>
<td>1.61 (1.27, 1.99)</td>
<td>2.68 (2.17, 3.19)</td>
</tr>
<tr>
<td>Informality</td>
<td>7.55 (6.54, 8.77)</td>
<td>6.87 (4.13, 7.55)</td>
</tr>
<tr>
<td><strong>Weighted estimates</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Poverty</td>
<td>.258 (.25, .265)</td>
<td>.276 (.263, .287)</td>
</tr>
<tr>
<td>Women’s empowerment</td>
<td>.129 (.127, .131)</td>
<td>.16 (.157, .163)</td>
</tr>
<tr>
<td>Informality</td>
<td>.132 (.122, .144)</td>
<td>.19 (.173, .201)</td>
</tr>
</tbody>
</table>

(*) Point estimates under quadratic loss. Between brackets below each point estimate: 95% credible intervals

To approximate the impact of microcredit on the population living in a municipality, average treatment effects were also estimated using population weights at the municipal level. As shown in Table 1, these estimates point to a marginal increase in UBN poverty when comparing heavily populated municipalities, together with an increase in informality and women’s empowerment in densely populated municipalities. The implicit hypothesis in this exercise is that individuals are perfectly homogenous within each municipality, which is of course a strong hypothesis.

In terms of post-estimation statistics (Table 2), the value of Efron’s pseudo-R2 of close to 50% suggests an acceptable model fit for the spatial probit models; the spatial correlation is higher for the spatial error models in the survey model of informality and the balancing tests in general point to the non-rejection of the null of balanced control covariates; nevertheless, the evidence of compliance with the balancing property is weaker for the variable estimated with survey data (informality), raising a concern of whether the propensity score is well estimated for this variable. The results of the Geweke convergence diagnostic (Geweke, 1992) suggest a good chain convergence in the case of poverty and women’s empowerment, but not in the case of informality, casting doubt on the chain convergence for this variable and showing again that care must be taken when interpreting the results about the effect of microfinance on informality.

To further evaluate the possibility of spurious erroneous associations, Appendix II runs a falsification test for the BS-PSM algorithm, based on the pre-specified false hypotheses that microfinance is causally related to the percentage of people with deafness in a municipality. The results showed a lack of confirmation of the improbable link of microfinance with deafness, supporting the conclusions about the associations of interest in the study.
Finally, Appendix III compares the estimation of the ATE with and without spatial information. The results show that a posterior estimation of the spatial correlation $\rho$ that includes zero with a 95% probability does not affect the estimation of SATE, but nonetheless the SATE is sensitive to the exclusion of spatial effects during the matching.

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(*) Between brackets below each point estimate: 95% credible intervals  
(†) Bayesian point estimates. The term $x_0$ is the constant in the spatial models  
(‡) Bayesian p-values for the null of balanced variable  
(♦) p-values for the null of equal mean in the fractions of the chain. The test was run using the 50th centile of the SATE chains and fractions of 10% and 50% at the start and the end of the chain, respectively.
V. Conclusions and policy implications

A Bayesian Spatial-Propensity Score Matching estimator was proposed to evaluate regional treatment effects of microfinance on poverty, informality and women’s empowerment 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 the municipal level was found with the BS-PSM estimator for Bolivia, using a poverty indicator based on unsatisfied basic needs. The Bayesian SATE estimator also showed strong evidence of female empowerment through decision-making at the household level in municipalities with microfinance access in Bolivia. The favorable effect of microfinance on female empowerment is similar to that obtained by inter alia Rahman (1986), Pitt and Khandker (1998), Pitt et al. (2006) or Swain and Wallentin (2009). These findings are conditional on the fulfillment of an unconfoundedness assumption (no other unmeasured confounders besides the observed 9 covariates in the spatial probit model) and on the assumptions behind ecological regression; see e.g. Gelman et al. (2001) for a discussion. To avoid the assumptions of ecological regression future studies can explore the possibility of expanding the BS-PSM algorithm with multilevel data through the inclusion of individual-level data at the regional level and the use of procedures described in inter alia Li et al. (2013).

The results for Bolivia also suggest that the possible cost of poverty reduction and female empowerment could have been an increase in informality. As currently the access to micro-credit in Bolivia identifies income generation (payment capacity) as the main requirement that must be evaluated when granting a loan, regardless of whether the economic activity of the applicant has all legal documents for formal operation, microfinance could be adding up to the structural factors that cause informality in Bolivia—regulatory burden, weak institutions and lack of perceived benefits for being formal (World Bank, 2009). Nevertheless, as the evaluation of the regional impact of microfinance on informality with BS-PSM is based on household survey data, which does not cover all the regions of Bolivia, and suffers from estimation problems related to unbalanced covariates and non-convergent chains, the results on informality cannot be considered conclusive.

In terms of policy relevance for Bolivia, the results of impact evaluation are useful to inform evidence-based policy decisions for the New Development Plan and the New Law of Financial Services of this country. The New Development Plan of Bolivia up to 2025 aims to develop a financial system for integral development committed to poverty eradication through loan provision, financial services and financial access. In the case of the New Law of Financial Services, it goes beyond prudential regulation and seeks to improve financial access and income for low-income populations, as states that financial access must be on a basis of equal treatment, without discrimination because of age, gender, race, religion or cultural identity. In this context, the findings of positive regional effects of microfinance for women’s empowerment and poverty suggest that the government has to encourage the environment for microfinance and further expand financial access.

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5 It is important to note that even if BS-PSM can be used for bias removal, it fails to treat the endogeneity. In the case of poverty, for example, the outcome can influence the probability of being selected (treated) for financial access.

and loan provision at the municipal level, since the possible cost of increasing informality may not be relevant compared with the primary objective of reducing poverty, particularly in light of the recent policies of the Bolivian government aimed to promote socio-economic development through financial services. More research is needed to properly identify the reasons for the existence of regions with little or no financial access in Bolivia and thus formulate policies of financial provision through government banks that complement the financial services provided by private financial institutions.

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 BS-PSM algorithm, making it possible to perform a rigorous inferential analysis based on credible intervals and not only on point estimates of the average treatment effects.

Despite these clear advantages, it is worth noting that BS-PSM identifies treatment effects at the regional level assuming that these effects are caused by spillovers, without explicitly identifying the source of the spillover effects at the household or individual level. Future work can concentrate on improving this limitation in an effort to identify the mechanisms behind the impact of microfinance at the regional level, because –as indicated by one of the external reviewers– (i) if the channels are related to intra-household allocation, a proper policy will be give more power to women to control their resources, (ii) but if the channels are ancillary industries, there is a need to strength the human resources and institutions that provide financial services in remote areas; and finally, (iii) if the transmission channels are caused by impacts on consumption that have local multiplier effects, then no additional policy may be needed, as the multiplier mechanisms are already working. The existence of these transmission channels could explain the existence of aggregate effects at the regional level, despite the fact of a lack of effects at the household level, making both results compatible with each other.
References


Appendix I

Bayesian spatial propensity score matching estimator of spatial average treatment effects

**Spatial probit models.**

Let \( \mathbf{t} \) be a \( n \times 1 \) vector of 0,1 binary values that reflect the absence/presence of a treatment in a region \( i = 1, \ldots, n \). A Spatial Error Model (SEM) with spatial influence captured through an error term \( \varepsilon \) is

\[
\begin{align*}
\mathbf{t} &= \mathbf{X}\beta + \varepsilon, \\
\varepsilon &= \rho \mathbf{W}\varepsilon + \nu, \quad \nu \sim \mathcal{N}(0, \sigma_v^2 \mathbf{I}_n),
\end{align*}
\]

for \( \rho \) a spatial correlation coefficient, \( \mathbf{W} \) a \( n \times n \) row-stochastic proximity matrix and \( \mathbf{X} \) a \( n \times p \) matrix of \( p \) control covariates

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

The SEM model is consistent with spatially autocorrelated shocks in the error term (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; see Corrado and Fingleton (2012).

The Bayesian latent variable treatment for modeling this type of spatial limited dependent variables treats the binary 0,1 observations in \( \mathbf{t} \) as indicators of a latent, unobserved (net) utility of a spatial agent in an \( i \)-region. Formally, based on the difference in utilities \( u_{1i} - u_{0i} \), \( i = 1, \ldots, n \), associated with observed 0,1 choice indicators, the probit model assumes that the difference \( t_i^* = u_{1i} - u_{0i} \) follows a Gauss-Laplace distribution, and, as \( t_i^* \) is unobservable, then \( t_i = 1 \) if \( t_i^* \geq 0 \) and \( t = 0 \) if \( t_i^* < 0 \). This implies \( \mathbb{P}(t_i = 1) = \mathbb{P}(u_{1i} \geq u_{0i}) = \mathbb{P}(t_i^* \geq 0) \). Thus, a general likelihood for the SEM model is,

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7 See Smith and LeSage (2004) for a detailed discussion on the Bayesian latent variable treatment of probit models. Smith and LeSage (2004) motivate the basic probit model in terms of an explicit choice-theoretic context involving individual behavioral units which exhibit spatial interaction effects due to the varying spatial location of the decision makers. That is, individuals located at similar points in space may tend to exhibit similar choice behavior with a spatial grouping of individuals by region based on the assumption that that individuals within each region are homogeneous and thus the spatial dependencies and heteroscedastic effects occur at the regional level.) Albert and Chib (1993) provide a less formal economic interpretation and view the latent variable simply as unobserved values associated with observed choice events.
\[ \mathcal{L}(t, X | \beta, \rho, \sigma_u^2) = \frac{1}{2 \pi \sigma_u^{2n/2}} |I_n - \rho W| \exp \left\{ -\frac{1}{\sigma_u^2} \epsilon^\prime \epsilon \right\}, \]

for \( \epsilon = (I_n - \rho W)(t - X \beta) \). With a diffuse prior for \( \beta, \rho, \sigma_u^2 \), a joint posterior for this parameters is,

\[ \mathbb{P}(\beta, \rho, \sigma_u^2 | t, X) \propto |I_n - \rho W| \sigma_u^{-(n+1)} \exp \left\{ -\frac{1}{\sigma_u^2} \epsilon^\prime \epsilon \right\}, \]

with a kernel,

\[ \mathbb{P}(\sigma_u^2 | \beta, \rho) \propto \sigma_u^{-(n+1)} \exp \left\{ -\frac{1}{\sigma_u^2} \epsilon^\prime \epsilon \right\}, \]

for the conditional posterior of \( \sigma_u^2 \) and,

\[ \mathbb{P}(\beta | \rho, \sigma_u^2) \sim \mathcal{N}(\beta, \sigma_u^2 (X'B'BX)^{-1}), \]

\[ \bar{\beta} = (X'B'BX)^{-1}(X'B'Bt), \]

\[ B = (I_n - \rho W), \]

for the conditional multivariate normal distribution of \( \beta \). The conditional distribution of \( \rho \) given \( \beta \) and \( \sigma_u^2 \) is,

\[ \mathbb{P}(\rho | \beta, \sigma_u^2) \propto |I_n - \rho W| \sigma_u^{-(n+1)} \exp \left\{ -\frac{1}{\sigma_u^2} \epsilon^\prime \epsilon \right\}. \]

LeSage (2000) proposed a Markov Chain Monte Carlo (MCMC) sampler to draw samples from this last distribution. See also LeSage and Pace (2009).

**Matching.**

Matching estimators contrast the outcome of a treated individual—a region, in this case—with outcomes of comparison group members (Caliendo and Kopeinig, 2008). Let \( \hat{p} := \mathbb{P}(t_i = 1) = f(\rho W e, X \bar{\beta}) \) be the estimated probabilities of a spatial probit model. A traditional pairwise nearest-neighbor matching between treated and untreated regions can be implemented with

\[ C_{nn}(\hat{p}) = \min_j \| \hat{p}_i - \hat{p}_j \|, \quad j \in n_0, \]

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 $\delta$ be a proximity measure among regions—captured through the distance matrix $W$—, if $\delta$ is considered when performing the matching,

$$C_{sc}(\hat{p}, W) = \min_j \|\hat{p}_i - \delta_j \hat{p}_j\|, \quad j \in n_0,$$

the propensity score $\hat{p}_i$ of a $i$-treated region is compared only with the propensity scores of nearby untreated regions: $\delta_j$ 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. Thus, 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 $\|\hat{p}_i - \delta_j \hat{p}_j\|, j \in n_0$). Applying a spatial caliper matching means taking into account spatial effects twice: (1) during the estimation of the propensity score, and (2) during the matching.

**Spatial Average Treatment Effect (SATE)**

The spatial (regional) average treatment effect (SATE) is,

$$\text{SATE} := \theta_u = \mathcal{M}(t, W, X, y, \Theta),$$

$$= \mathbb{E}_{W,\theta}\{(y_{i\mid t_i = 1, X_{1i} = x_1, ..., X_{pi} = x_p}) - (y_{i\mid t_i = 0, X_{1i} = x_1, ..., X_{pi} = x_p})\},$$

for a regional outcome variable $y$, a matching function equal to $\mathcal{M}(\cdot)$ and $\{\beta, \rho, \sigma_p^2\} \in \Theta$ a stacked vector of parameters of the spatial discrete choice model.

**Weighted Spatial Average Treatment Effect (wSATE).**

A weighted estimator of the spatial average treatment effect ($\theta_\omega$) can be calculated with,

$$\theta_\omega = \mathcal{M}_\omega(t, W, X, y, \Theta, \omega),$$

$$= \sum_{\mathcal{A}_i} \frac{n_i}{N_{\mathcal{A}_i}} \mathbb{E}_{W,\theta}(y_{i\mid t_i = 1, X_{1i} = x_1, ..., X_{pi} = x_p}) - \sum_{\mathcal{A}_j} \frac{n_j}{N_{\mathcal{A}_j}} \mathbb{E}_{W,\theta}(y_{i\mid t_i = 0, X_{1i} = x_1, ..., X_{pi} = x_p})$$

using a weighted matching $\mathcal{M}_\omega$ function with weights $\omega = N^{-1}n$, for $n_i$ the population in a region $i$, $N_{\mathcal{A}_i} = \sum_{\mathcal{A}_i} n_i$ in a subset $\mathcal{A}_i$ of treated regions, and $N_{\mathcal{A}_j} = \sum_{\mathcal{A}_j} n_j$ in the subset of $j$-untreated regions. A similar estimator was proposed by Zanutto (2006) for the estimation of the average difference in outcomes between treated and control units in the context of a stratified sampling design. The
unweighted estimator $\hat{\theta}_u$ is useful to approximate the overall treatment effects at the regional level; $\hat{\theta}_w$ in turn approximates treatment effects in the population living in a region.

**Density estimation of SATE**

Let $\{p^{(1)}, p^{(2)}, \ldots, p^{(g)}\}$ be $g$ estimated probabilities based on the draws of $\mathbb{P}(\beta^{(g)}|\rho, \sigma^2)$ and $\mathbb{P}(\rho^{(g)}|\beta, \sigma^2)$ in the spatial probit model, then,

$$C_{\text{ac}}(p^{(g)}, W) = \min_j \left\| p_j^{(g)} - \delta_j p_j^{(g)} \right\|,$$

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

$$\{M(t, W, X, y, \theta^{(g)})\}_{g=1}^G$$

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

**Point estimators and credible intervals.**

Let $\theta$ be a weighted/unweighted SATE estimator, $\theta \in \{\theta_u, \theta_w\}$. A Bayesian point estimator of the SATE $\hat{\theta}$ is the value of $\theta$ that minimizes the expected value of a loss function $\ell(\theta, \hat{\theta})$, where the expectation is taken over the posterior distribution of $\theta$, $\pi(\theta|\mathcal{D})$,

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

Under quadratic loss, $\ell(\theta, \hat{\theta}) = (\theta - \hat{\theta})^2$,

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

Differentiating with respect to $\hat{\theta}$ and setting the derivate to zero,

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

i.e. the optimal point estimator under quadratic loss is the mean of the simulated posterior distribution of $\theta$; see Geweke (2005) or Gill (2007). A Bayesian credible interval $C_{\theta, \gamma}$ for the SATE with a credibility $\gamma = 1 - \alpha$ can be obtained with a sub-region of the probability space parametrized by $\theta \in \Theta$, where,

$$\int_{C_{\theta, \gamma}} \pi(\theta|\mathcal{D}) d\theta = \gamma.$$

See inter alia Shalloway (2014).
Appendix II
Falsification test for the BS-PSM Algorithm

A falsification test was run to evaluate possible false positives of the BS-PSM algorithm. The pre-specified falsification hypotheses is that microfinance is causally related to the percentage of people with deafness in a municipality, an hypotheses which is highly unlikely to be true.

Figure A.1 shows the observed differences in deafness of municipalities with and without access to microfinance; the descriptive results point to a higher percentage of people with deafness in municipalities without access to microfinance (.75%) compared to municipalities with access to microfinance (.65%). Figure A.2 shows the results of the Bayesian estimation of the SATE of microfinance on deafness, based on the BS-PSM algorithm. The 95% credible intervals cross zero frequently, providing no evidence in favor of the pre-specified false hypotheses. The lack of confirmation of an improbable link of microfinance with deafness, supports the conclusions about the associations of interest in the study.

Figure A.1: Observed differences in deafness of municipalities with and without access to microfinance.

Figure A.2: Average difference in deafness (of municipalities with and without access to microfinance) estimated with BS-PSM
Appendix III
Sensitivity to spatial information

Sensitivity of the results to the inclusion of spatial information was evaluated by changing the prior of the spatial correlation coefficient of the probit function to $\rho \sim \mathcal{U}(-1,0.1)$ (which includes no spatial correlation) instead of $\rho \sim \mathcal{U}(0,1)$ (positive spatial correlation a priori) and using a conventional nearest neighbor matching instead of the spatial caliper matching of the study.

The posterior estimation of $\rho$ includes zero with a 95% probability (see Figures A.4b, A.6b and A.8b), i.e. no spatial correlation was assumed a priori in the probit model that was used to estimate the propensity scores. The estimates of SATE based on the assumption of no spatial correlation do not seem to be affected by this assumption, as the results with and without spatial information are almost exactly the same, as can be seeing by a comparison of Figures A.3d with A.4d, A.5d with A.6.d and A.7d with A.8.d).

In contrast to the previous results, the estimation based on a traditional non-spatial nearest neighbor matching produce a multimodal estimation of the regional ATE. This last result suggests that the estimation of the SATE is sensitive to the inclusion/exclusion of spatial effects during the matching. See and compare Figures A.3d with A.3f, A.4d with A.4f, A.5d with A.5f, A.6d with A.6f, A.7d with A.7f and A.8d with A.8f.
Figure A.3: Estimation of SATE for women’s empowerment with spatial information.
(a) MCMC runs of $\rho$ with a prior $\rho \sim \mathcal{U}(0,1)$. (b) Histogram of $\rho$. (c) MCMC runs of SATE with spatial caliper matching. (d) Histogram of SATE with spatial caliper matching. (e) MCMC runs of SATE without spatial matching. (f) Histogram of SATE without spatial matching.

Figure A.4: Estimation of SATE for women’s empowerment without spatial information.
(a) MCMC runs of $\rho$ with a prior $\rho \sim \mathcal{U}(-1,0,1)$. (b) Histogram of $\rho$. (c) MCMC runs of SATE with spatial caliper matching. (d) Histogram of SATE with spatial caliper matching. (e) MCMC runs of SATE without spatial matching. (f) Histogram of SATE without spatial matching.
Figure A.5: Estimation of SATE for poverty with spatial information.  
(a) MCMC runs of $\beta$ with a prior $\rho \sim \mathcal{U}(0,1)$.  
(b) Histogram of $\hat{\rho}$.  
(c) MCMC runs of SATE with spatial caliper matching.  
(d) Histogram of SATE with spatial caliper matching.  
(e) MCMC runs of SATE without spatial matching.  
(f) Histogram of SATE without spatial matching.

Figure A.6: Estimation of SATE for poverty without spatial information.  
(a) MCMC runs of $\beta$ with a prior $\rho \sim \mathcal{U}(-1,0,1)$.  
(b) Histogram of $\hat{\beta}$.  
(c) MCMC runs of SATE with spatial caliper matching.  
(d) Histogram of SATE with spatial caliper matching.  
(e) MCMC runs of SATE without spatial matching.  
(f) Histogram of SATE without spatial matching.
Figure A.7: Estimation of SATE for poverty with spatial information.
(a) MCMC runs of $\rho$ with a prior $\rho \sim \mathcal{U}(0,1)$. (b) Histogram of $\rho$. (c) MCMC runs of SATE with spatial caliper matching. (d) Histogram of SATE with spatial caliper matching. (e) MCMC runs of SATE without spatial matching. (f) Histogram of SATE without spatial matching.

Figure A.8: Estimation of SATE for poverty without spatial information.
(a) MCMC runs of $\rho$ with a prior $\rho \sim \mathcal{U}(-1,0.1)$. (b) Histogram of $\rho$. (c) MCMC runs of SATE with spatial caliper matching. (d) Histogram of SATE with spatial caliper matching. (e) MCMC runs of SATE without spatial matching. (f) Histogram of SATE without spatial matching.