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Evaluating The Effectiveness Of Financial Intervention For Improved Living Conditions



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# EVALUATING THE EFFECTIVENESS OF FINANCIAL INTERVENTION FOR IMPROVED LIVING CONDITIONS

By

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ABSTRACT

The purpose of this investigation is to find the causal effect of financial intervention on socioeconomic factors of the communities under the India SKS bank microfinance institution. The data being analyzed comes from a randomized experiment in India that implemented a mandatory health insurance purchase with renewal of loan on households in the Bidar and Gulbarga districts from 2006 to 2010. The focus is to evaluate the intervention effect of the mandatory health insurance purchase on socioeconomic factors, annual total household's health expense and others. The evaluation is done by collecting the data using an experimental plan and performing the causal inference from the collected observations. The methodology involves matching the treatment group units required the mandatory health insurance and the control group units not required it. The project creates the paired data in the treatment and control groups by using the matching methods to estimate the treatment effect to evaluate the effectiveness of the financial intervention. Evidence of a positive treatment effect in different countries could shape the economic policy to improve global living conditions.

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# INTRODUCTION

This project focuses on a specific financial intervention by evaluating the effectiveness of mandatory health insurance on total annual household health expenses from a randomized experiment. The purpose of this research is to evaluate whether the mandatory health insurance purchase has a significant effect on improving the living conditions of people. The investigation is using the data collected from a randomized experiment where the treatment group households received the health insurance but the control group did not receive it (Banerjee et al., 2018). Strong significant evidence could support a future mandatory health insurance policy. The research question is how effective was the mandatory health insurance purchase in reducing total health expenses. It is hypothesized that the purchase of mandatory health insurance had a positive effect in lowering total annual health expenses.

# BACKGROUND & LITERATURE REVIEW

A loan from the SKS India Microfinance institution came with an additional purchase of mandatory health insurance for the treatment households and the control group did not have the requirement for an additional purchase of the mandatory health insurance.[1] The division of treatment and control group households was performed by randomization (Banerjee et al., 2018).

The total variables for this data are: SKS client ID number, village ID number, stratum number, treatment group identification, number of members in each household, baseline total health expense, baseline hospitalization expense, baseline indicator of having formal health insurance available, baseline indicator of owning formal health insurance, baseline total household consumption, endline indicator of overnight stay at a hospital, endline total health expense, endline total expenses paid themselves, endline indicator of received medical care, endline indicator of consultation with any medical facility, endline indicator of consultation with bhopa (traditional healer), endline indicator of overnight stay in a facility, and endline number of nights stayed in a facility (Banerjee et al., 2014). All these variables were obtained from survey questions asking for information about the previous year (Banerjee et al., 2014). The currency used for these variables was rupees[2] (Banerjee et al., 2018). Baseline variables were recorded after randomization but before treatment (Banerjee et al., 2018). Endline variables were recorded after randomization and about two years after treatment was implemented in the treatment group (Banerjee et al., 2018).

[1] The health insurance was 525 rupees and the average loan renewal was 10,300 rupees (Banerjee, et al., 2018). The mandatory health insurance purchase was required only for new clients and clients renewing their loans at the start of the policy (Banerjee, et al., 2018). The policy covered catastrophic incidents, hospitalization, and maternity expenses (Banerjee, et al., 2018). The clients could go to approved health facilities for treatment or claim reimbursement for treatment at other facilities (Banerjee et al., 2018).

[2] 525 rupees was thirteen US dollars and 300 rupees was seven US dollars for the 2007 exchange rates (Banerjee, et al., 2018). About 41 rupees was one US dollar for the 2007 exchange rates (Banerjee, et al., 2018).

The variables of focus for this project are total baseline and endline household health expenses, stratum number, and the number of members in each household for the treatment group and control group. Baseline variables were obtained before receiving mandatory health insurance and endline variables were obtained after receiving it. The treatment group households have both baseline and endline total health expenses. On the other hand, the control group households have only baseline total health expense. The goal is to estimate the endline total health expenses for the households in the control group using statistical methodologies. Finally, the comparison of the baseline and the endline health expenses will demonstrate the mandatory health insurance program effectiveness.

## METHODS & APPROACH

### Data

The research article, “A Multi-faceted Program Causes Lasting Progress for the Very Poor: Evidence from Six Countries,” describes six randomized financial intervention experiments for testing the effectiveness of long-term escape from poverty (Banerjee et al., 2015). The countries were India, Ethiopia, Pakistan, Ghana, Honduras, and Peru (Banerjee et al., 2015). Each method of randomization from each of the six countries was different.

The data from a large sample in India of the six countries on the use of financial intervention in a randomized experiment over the course of years was used in this project as the primary data. The sample is the 5,366 randomly chosen households in the regions chosen in India (Banerjee et al., 2014). The materials used in this project were the primary data and R Computer Software.

### Randomization

Randomization is a method to fairly divide the sample into a treatment group and a control group. The treatment group will receive the treatment and the control group will not receive the treatment but serves as a comparison to see the effect of the treatment. To avoid bias, it is ideal to have the treatment and control divided up equally, which means they are selected with equal chance. The equal chance is performed using randomization. There should be no unintentional influence in the selection. This way the treatment group and control group will be about the same in sample size and in characteristics of the subjects before the treatment is given.

Particularly for the country of focus for this project, India, the research article, “How Much Do Existing Borrowers Value Microfinance? Evidence from an Experiment on Bundling

Microcredit and Insurance” (Banerjee, et. al., 2018) provided more information about the experiment in India as well as the raw data. India started with 201 candidate villages in Bidar and Gulbarga district in Northern Karnataka then used stratified sampling to divide into treatment and control villages based on branch and number of clients (Banerjee et al., 2018). Bidar and Gulbarga are two districts in Northern Karnataka and Karnataka is a rural area with one of India's leading microfinance organizations during that time for SKS (Banerjee et al., 2018).

**Figure 1.1**

**India Random Sampling**

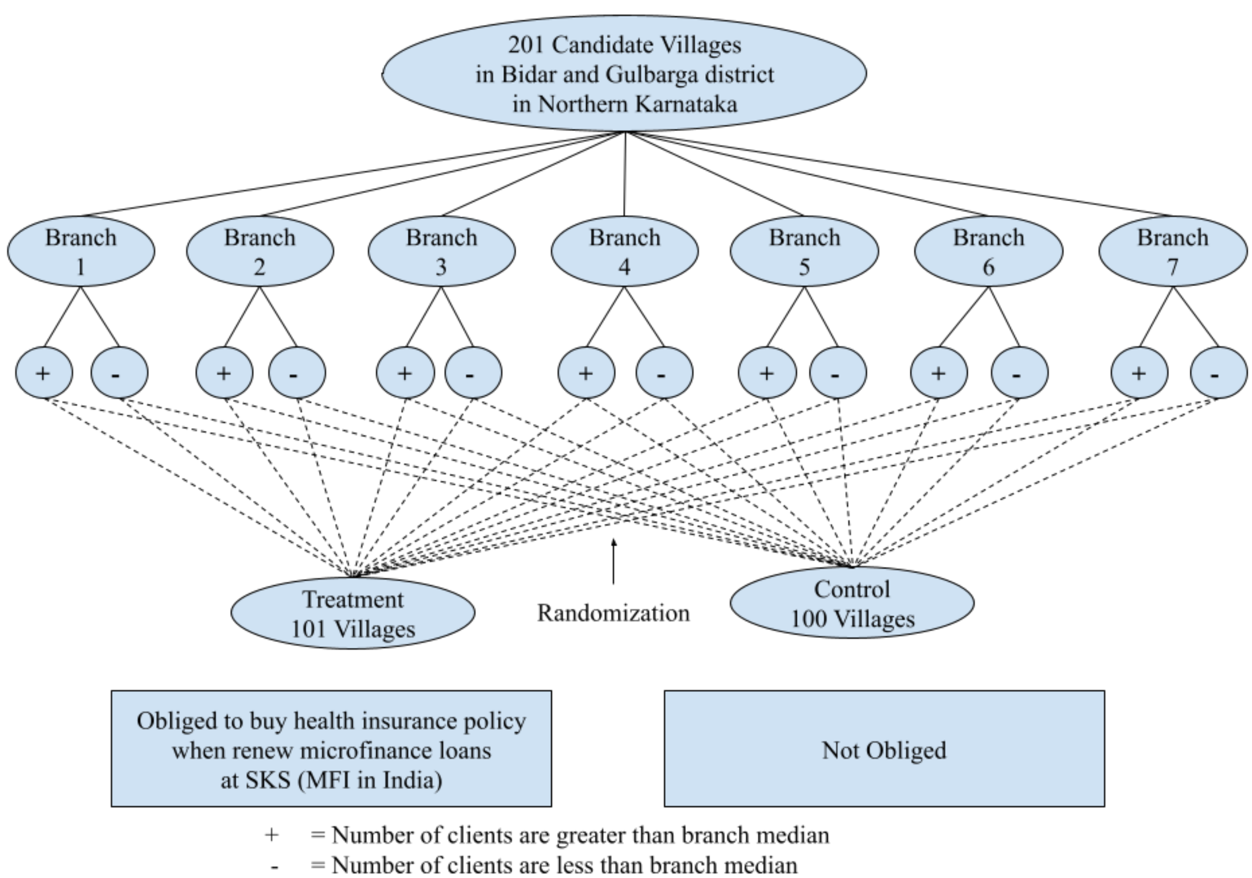


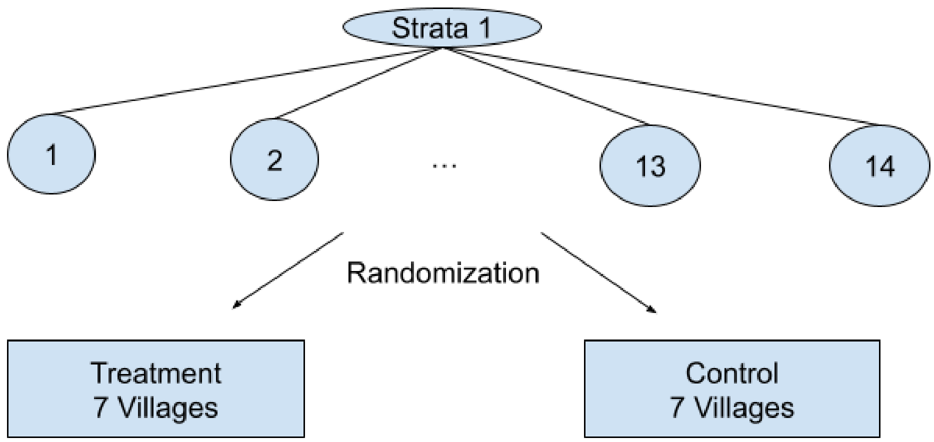
Figure 1.1[3] is describing this stratified randomization process in dividing 201 villages from two districts in India into 101 treatment villages and 100 control villages. Within the stratification, the 201 candidate villages were divided by their identified branch of seven branches from the microfinance institution (MFI), SKS in India for an even geographical distribution (Banerjee et al., 2018). From there, the villages were then grouped into two groups within each of the seven branches, either the village had a greater number of clients than their branch median or the village had less number of clients than their branch median (Banerjee et al., 2018). Since the SKS clients are defined as households, the number of clients greater than the branch median would mean a greater number of households in a village, a greater village size, and the number of clients less than the branch median would mean a smaller village size. This means the client stratification was for an equal distribution of village size within the treatment group, therefore the control group as well. For an approximately equal number of villages in each group, 101 villages were randomly selected from each of the fourteen strata and the remaining 100 villages were to be the control villages (Banerjee et al., 2018).

Then a stata random number generator was used to randomly select villages as treatment and those not selected were the control villages (Banerjee et al., 2018). In total, there are fourteen stratas with each strata having about an equal number of control and treatment villages. Each village is grouped together, meaning all households in the same village will be in either control or treatment together. This was chosen intentionally to have those SKS operation centers within a village in close proximity to those receiving either the same treatment or control (Banerjee et al., 2018). The treatment village was obliged to buy the health insurance policy when they renewed microfinance loans at SKS, the MFI in India, and the control village was not obliged. Even if the

[3] The diagrams in Appendix 1.2 - 1.6 show each method of randomization for the other five countries.

control group was not obliged by the SKS health insurance policy, they possibly were insured elsewhere (Banerjee et al., 2018).

**Figure 2**




Strata are the groups that villages are in before randomizing within each group. Figure 2 is an example of how randomization was performed on an example strata to divide into treatment and control villages. Strata 1 has fourteen villages with seven villages randomly chosen to be treatment villages and the rest of the seven to be control villages.

## Table

In the raw data, there were responses to various questions used by the surveyors in the experiment to determine the characteristics and socioeconomic status of the subjects before and after the treatment was given (Banerjee et al., 2014). There were eighteen columns constructed into a table from the raw data files.[4]

[4] The table was constructed by referring to the survey source. The column names were determined after matching the question number from the survey to the variable name from the raw data.

Each column, household characteristics, with continuous variables that would be better comparable between control and treatment as a z-score were standardized. This means each individual characteristic was reduced by the mean of the group it belonged then divided by the standard deviation of the group it belonged to. Z-scores could be easier to interpret for continuous variables because, for example, two values each from two different groups could have what would appear a big difference of about 2000 in the original value and a small difference of about 0.1 in the z-score. In that z-score example, one of the group's scales is higher than the other so they are not very close to each other but both of the two values are close to their group's mean.

**The Goals**

The causal effect could answer the research question and can be estimated by the average treatment effect. The causal effect of mandatory health insurance purchase on total health expenses is calculated by subtracting the expected baseline total health expense from the expected endline total health expense. The average treatment effect cannot be calculated with missing endline total health expense values. With this challenge, the next step was determining a method in R to fill in missing values for the endline total health expense.

**Figure 3**

| X4 | X3 | X5 | X6 | X12 |
|---|---|---|---|---|
| 0 | 108 | 9 | 3320 | |
| 1 | 108 | 9 | 3480 | 960 |
| 0 | 109 | 6 | 6300 | |
| 1 | 109 | 6 | 6100 | 0 |
| 0 | 104 | 4 | 0 | |
| 1 | 104 | 4 | 340 | 900 |

The baseline and endline total health expenses for the treatment group were available. Only the baseline total health expense data was available for the control group. As shown in Figure 3, the endline total health expense data are the potential outcomes in red to be estimated from the available data in green by the matching method.

To fill in the missing endline total health expense values, matching must first take place between control group households and treatment group households with values close in the chosen matching variables obtained before the mandatory health insurance purchase was implemented.

**Why The Matching Method?**

With this data, the endline total health expense and baseline total health expense is important in understanding the treatment effect. The treatment effect is the effect of the mandatory health insurance purchase with the renewal of loans on total health expenses. To find the treatment effect, the values from before the implementation of the treatment and the values from after the implementation of the treatment must be compared. Baseline values are obtained before the treatment and endline values are obtained after the treatment with treatment being the mandatory health insurance purchase. Our treatment group has both baseline total health expense and endline total health expense. The control group has only baseline total health expense because the endline total health expense for the control group was not recorded after given the treatment since the control group did not receive the treatment.

For the following sections, baseline total health expense will be the matching variable for a clear example of the matching method, until the section on determining the final matching variables, when better-performing matching variables are explored. Since the control group does not have the endline total health expense values to measure the treatment effect, the goal is to fill those missing endline total health expense values using the treatment endline total health expense values. To do this, the matching method is used to match the control baseline total health expense to the treatment baseline total health expense. By doing so, the treatment and control are matched based on a household characteristic recorded before the treatment was implemented (Rubin, 1974). With a similar starting point in total health expense before treatment, the treatment group household endline total health expense can be inserted into its matched control group household endline total health expense (Rubin, 1974).

**What Does Matching Method Do?**

The results of the matching method will return one group. Each household will have a baseline total health expense, observed before the treatment was implemented, and an endline total health expense, observed after the treatment was implemented. Instead of using each household as either a control value or a treatment value, the matching returns a paired group. A paired group is where the subjects from the treatment group and control group are dependent on each other. In this case, the groups are dependent because the observations before and after the treatment was implemented will be compared using the same household. Each household will have a control value, being baseline total health expense, and a treatment value, being endline total health expense. Each household is generating a paired data consisting of the baseline and the endline total health expenses. Then, the total number of paired data is the total number of households in the control and treatment groups. A paired group has more power than a group independent of each other because there is less variance in characteristics not of interest between the comparison so that the treatment effect can be more clearly due to the outcome of interest, endline total health expense (Rubin, 1974).[5]

**The Steps for the Goal**

To determine which variables to match by, a linear regression can be performed to identify the baseline variables that have a causal effect on the endline total health expense. The determination of the optimum match of a control group household to a treatment group household is found by finding the closest match in terms of the values of the variables matched by. The matches are used to fill in the control group household after the mandatory health insurance purchase values with its paired treatment group household after the mandatory health insurance purchase values so that the control group and treatment group have endline total health expense values.

The reason for filling in missing values in the endline total health expense column is to calculate the average treatment effect. The average treatment effect is calculated by first taking the difference between the endline and the baseline measurements by subtracting the baseline

[5] It should be noted that using this matching method, means that the pairs will have similar baseline total health expense and the same endline total health expense.

from the endline. The average treatment effect is the average of all the differences. The mandatory health insurance would have a causal effect if the average treatment effect is different from zero. If the average treatment effect is negative, the mandatory health insurance would have a positive effect on total health expense. On the other hand, if the average treatment effect is positive, the mandatory health insurance would have a negative effect on total health expense. The contrast of negative and positive is because of the calculation of the average treatment effect which is the average of the endline minus the baseline. If, for example, the average treatment effect is positive, this means the endline is greater than the baseline. This however, has a negative effect because if the endline is greater than the baseline, this means that total health expenses increased after the mandatory health insurance purchase.

## ANALYSIS AND RESULTS

The data after preparation of the data consisted of 18 total variables. There are 5366 total households with 2734 being treatment households and 2632 being control households. The variables of interest that were used throughout the project were baseline total health expense, endline total health expense, household size, stratum number, and the variable indicating whether the household was part of the control group or the treatment group.

**Figure 4**

| X4 | X3 | X5 | X6 | X12 |
|---:|---:|---:|---:|---:|
| 0 | 108 | 9 | 3320 | 860 |
| 1 | 108 | 9 | 3480 | 960 |
| 0 | 109 | 6 | 6300 | 1890 |
| 1 | 109 | 6 | 6100 | 0 |
| 0 | 104 | 4 | 0 | 710 |
| 1 | 104 | 4 | 340 | 900 |

Figure 4 is an example of six households from the data containing only the variables of interest without any z-score transformation. The household is from the control group if X4 is zero and it is from the treatment group if X4 is one. For simplicity, the X4 variable will be called the treatment indicator. X3 will be one of fourteen numbers that indicate the stratum number, or their group before randomization. The number is not quantitative, it is only the name given for the stratum group. X5 is the baseline number of members in the household that from now on will be called household size. X6 is the baseline annual total health expense in rupees from the year previous to when the data was obtained. From now on, this variable will be called baseline total health expense. X12 is the endline annual total health expense in rupees from the year previous to when the data was obtained. From now on, this variable will be called endline total health expense.

It was established that a matching method will be used to fill in the missing values with the available values. There is a matching package in R that was used called MatchIt.

**MatchIt Package Explanation**

MatchIt is an R package that contains some matching methods to match the control household baseline total health expense to the closest treatment household baseline total health expense. Missing values were held into account because the MatchIt package in R that was used, will not match by column if that column had missing values. This meant that any missing values for baseline total health expense were removed before performing the matching function that matched by baseline total health expense.

From MatchIt, new columns were created including distance, weights, and subclass. Distance is the distance between the propensity scores that is, by default, generated by a generalized linear model (Viola, 2009). For this example, the propensity score is the probability that the household is from the control or treatment group given their baseline total health expense (Viola, 2009). MatchIt selects the best control matches that are not matched yet, based on the closest propensity score to treatment from largest to smallest (Viola, 2009). At first, it was discovered that distance was the same for all when using just baseline total health expense to match, this was because baseline total health expense was not significant in predicting the treatment column, as it was learned later on from learning more about the MatchIt package. Subclass are the groups of matches. The corresponding pairs have the same subclass. Those households not matched after MatchIt were discarded.

## MatchIt Arguments

The arguments focused on were formula, data, method, and distance. The formula is inputted to match the treatment variable by the baseline total health expense variable. The data comes from all the households from our new table described previously with the appropriate z-score values. Possible matching methods are exact, full, genetic, optimal, subclass, cardinality, and nearest (Viola, 2009). Exact is exact matching, full is full matching, genetic is genetic matching, optimal is optimal matching, subclass is subclassification, cardinality is cardinality matching, and nearest is nearest neighbor matching, which is the default argument (Viola, 2009). Cardinality was eliminated from the exploration process because it does not form pairs, cem because it would discard more households, and exact because it would also discard more households. Full, cem, genetic, nearest, optimal, and subclass were tested. Full and nearest achieved the most successful MatchIt based on sample size after matching and the distance between the pairs' covariates on average. The difference between full and near is that all households with full receive at least one match and the sum of the absolute distances between the treated and control units in each subclass is as small as possible while nearest possibly could result in large standardized pair distances.

For the project's intent of matching the most control to treatment households with closeness in the values of the matches, nearest was chosen. The nearest method is one-to-one nearest neighbor matching without replacement on a propensity score that selects the best control matches for each individual in the treatment group (Viola, 2009). Using the nearest method with distance as the default, generalized linear model, to estimate propensity score, could result in very different values for the pairs because each match is selected without considering the other matches happening afterward (Viola, 2009).

The propensity score was not used to match in this project because of the high imbalance in the values of the pairs. This is why it was decided to prioritize matching closely on specific covariates. Mahalanobis or caliper could be used to match by covariates directly (Viola, 2009). Caliper is used to achieve smaller standardized pair distances and can also be used on propensity scores. To try to combat these disadvantages, a caliper was used with both nearest and full, as well as distance Mahalanobis with nearest as well. The argument specified for caliper was to match baseline total health expense only with pairs within the specified units of each treatment and control pair, which was 0.1 since z-scores range from about negative three to positive three.

**Successful MatchIt Performance**

Successful MatchIt performance is based on whether the covariates are balanced and whether the sample size is not significantly less after matching (Viola, 2009). This can be checked by calling the summary of the match function in R (Viola, 2009). From that function, a successful MatchIt performance can be identified by small standardized pair distances and large sample size after matching (Viola, 2009). Standardized pair distances are an average of how close the paired matching variable units are to each other (Viola, 2009).

**Matching Example**

The first examples were matched by baseline total health expense using the nearest method, generalized linear model, and a 0.1 caliper on baseline total health expense on the z-score dataset. It was determined from the matching of different-sized samples within the sample that the matches were within the second decimal point for baseline total health expense. 197 control households and 152 treatment households were removed for missing baseline total health expense values since a missing value cannot be used to match or calculate the average treatment effect. When the real values were replaced into the z-scores after matching and before filling in values, the same matches had a difference of about 2000 between the real values of the baseline total health expense.

**Determining the Final Matching Variables**

The response variable is the treatment indicator variable because the goal is to match pairs of one treatment household and one control household. The matching variable should be a baseline variable that affects the missing variable in calculating the average treatment effect, endline total health expense (Rubin, 2015). This way, the variable that affects the endline total health expense will be controlled for before the treatment is applied. The average treatment effect would better depict the causal effect of the mandatory health insurance on the endline total health expense, rather than the causal effect of mandatory health insurance and additional variables on the endline total health expense. The variable selection through linear regression determined the variables explaining the endline total household health expense. The outcome was that stratum number, household size, and baseline total health expense were three matching variables.

**Figure 5**

| X4 | X3 | X5 | X6 |
|---|---|---|---|
| 0 | 108 | 9 | 3320 |
| 1 | 108 | 9 | 3480 |
| 0 | 109 | 6 | 6300 |
| 1 | 109 | 6 | 6100 |
| 0 | 104 | 4 | 0 |
| 1 | 104 | 4 | 340 |

Figure 5 is an example of six households showing how the MatchIt method works. The two grey households are one match, the two yellow households are the second match, and the two orange households are the third match. The method inputted for this example was nearest, the distance was generalized linear model, and the caliper was specified to be zero for stratum number and household size and 1000 for baseline total health expense. With a caliper, this means that the matches are based on how close the variables of the matches are and must be within the specified number. Each match has a treatment household and a control household. Stratum number and household size are exactly the same for each match. The baseline total health expense is within 1000 for each pair.

After determining the matching variables and considering different matching methods, different combinations of these matching variables were inputted into the MatchIt package in R. After matching each different combination of matching variables, the performance of the matched pairs for the individual matching variable combinations was measured to determine which matching variable combination would be used to proceed to the filling step using the matches.

Stratum number and household size were chosen to match treatment and control households after attempting different combinations of baseline variables because they performed the best in retaining the most households, having pairs closest in the variable chosen (stratum number and household size), and controlling for more baseline variables affecting endline total health expense.

**Figure 6**

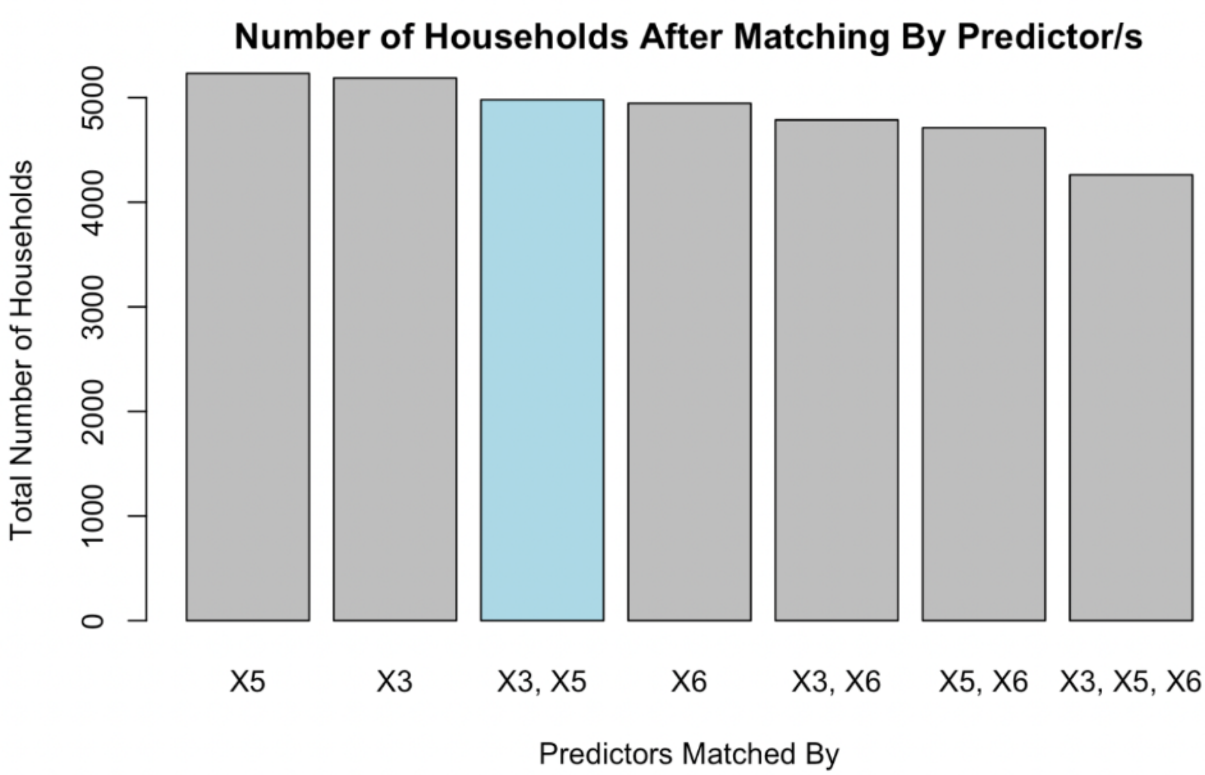



Figure 6 is a bar graph of the number of households after matching by each combination of matching variables selected. The horizontal axis contains each different combination of matching variables. The vertical axis is the number of households kept after matching. This is all the control households that were matched, the treatment households that were matched, and the treatment households that contained both the baseline and endline total health expense since these did not require filling in, meaning they did not need to be matched. The households discarded after matching were the control households that were not matched, therefore could not fill in the unavailable information in the endline total health expense, and the treatment households missing the baseline or endline total health expense because it could not be used to calculate the average treatment effect. The bar for stratum number and household size is fairly high. They retained more households compared to the other bars.

**The Final Match Method**

The matching variables for the final matching method were the household size and stratum number. The method was nearest neighbor, the distance was generalized linear model, and a caliper was set for the matches to be exact for the matching variables. Treatment households missing the endline total health expense values were removed before matching. No values were missing for household size or stratum number. The data put into the matchit function had the original values. The z-scores were not used because the matching variables household size and stratum number were both categorical values that could easily be compared without the conversion and the original values could be interpreted better.

**Example of Determining Average Treatment Effect After Matching**

**Figure 7.1**

| X6 | X12 |
|---|---|
| 3320 | |
| 6300 | |
| 0 | |

**Figure 7.2**

| X6 | X12 |
|---|---|
| 3480 | 960 |
| 6100 | 0 |
| 340 | 900 |

In this example, three control households are on the left in Figure 7.1 and three treatment households are on the right in Figure 7.2. As before, there are three matches of control and treatment by row. The first match is the first row of the control household with the first row of the treatment household and so on. The reds are the missing control endline total health expense and the blues are the available treatment endline total health expense.

**Figure 8.1**

| X6 | X12 |
|---:|---:|
| 3320 | 960 |
| 6300 | 0 |
| 0 | 900 |

**Figure 8.2**

| X6 | X12 |
|---:|---:|
| 3480 | 960 |
| 6100 | 0 |
| 340 | 900 |

In this example, the missing control endline total health expense is filled in with the potential observations. The endline total health expense from the treatment household are inputted into the endline total health expense for the treatment's matched control household. This means the unavailable information is filled in with the potential observations. Now each match of control households in Figure 8.1 and treatment households in Figure 8.2 have the same endline total health expense.

**Figure 9**

| X6 | X12 |
|---:|---:|
| 19540 | 3720 |

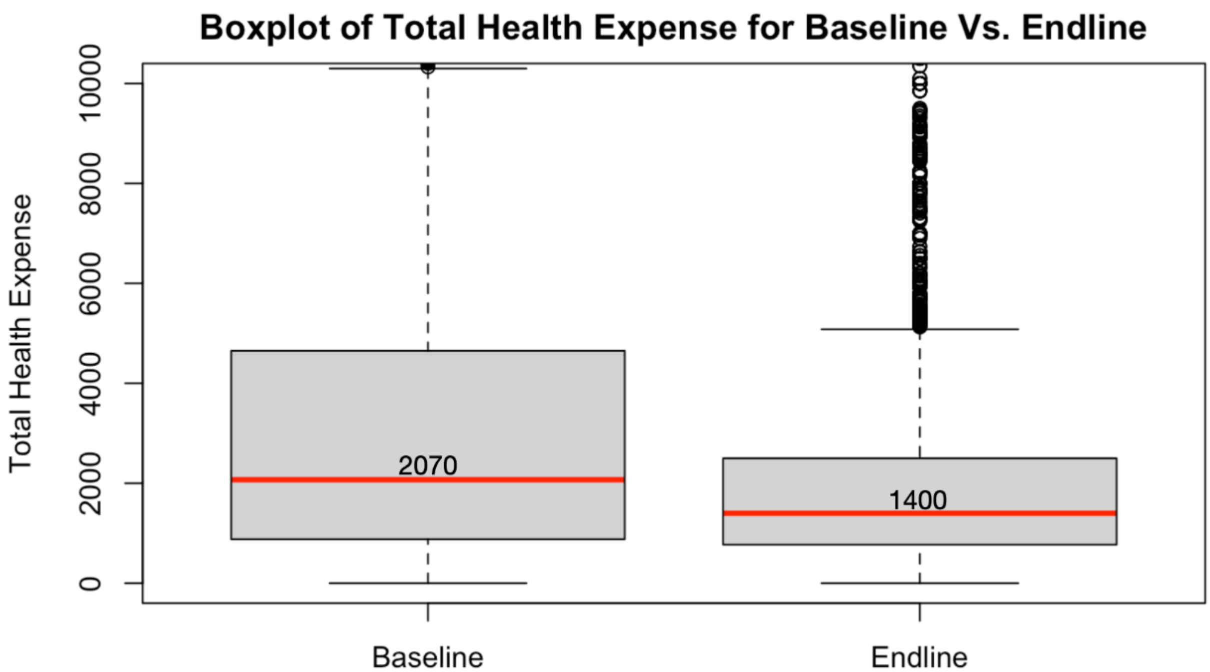
The average treatment effect is the average of the endline total health expense minus the baseline total health expense. The average treatment effect is an estimate of the causal effect of the mandatory health insurance purchase on the total health expenses. The first step of this calculation is to sum the baseline total health expense from the six households and then the sum of the endline total health expense for the six households. For the household example in Figure 9, the sum of the baseline total health expense is 19540 and the sum of the endline total health expense is 3720 for the six households. Then the baseline sum is subtracted from the endline sum. In the example, this is 19540 subtracted from 3720 which is -15820. The last step is to divide the difference by the total number of households. The average treatment effect for the six households is -15820 divided by six which is -2636.67.

**The Final Results After Matching**

The same steps performed to obtain the average treatment effect from the six example households were applied to all the households. The method for filling was done for all the matched households so that all control and treatment endline total health expenses within the matched pairs were the same. An additional step from the example is the treatment households that were not matched but had both the baseline and endline total health expenses were added to the new matched households dataset. This dataset of the final combination of households will be called the total households retained.

The average treatment effect for the total households retained is -1994.686. A Wilcoxon test for the endline and baseline total health expenses for the total households retained was performed to verify the average treatment effect. The p-value for the Wilcoxon test is about zero.

**Figure 10**




This boxplot in Figure 10 of the total health expenses from the total households retained visualizes the difference in endline and baseline from the average treatment effect calculation. There were many outliers in the baseline and endline original boxplot. For better visualization, the vertical scale was shortened to leave out the outliers exceeding the maximum top whisker. The median of the endline is 1400 while the median for the baseline is 2070. The third quartile and top whisker are also less for the endline than the baseline.

# CONCLUSION

The average treatment effect for the total households retained is -1994.686. The negative average treatment effect, suggests that on average, after the mandatory health insurance purchase with the loan, total health care expenses went down, indicating a positive effect. The findings are as expected in the hypothesis. This result is in support of the mandatory health insurance in terms of annual total health expense. This helps to understand one component of the data as a result of the mandatory health insurance.

The p-value of about zero from the Wilcoxon test means that it can be concluded that the endline and baseline total health expenses for the total households retained are significantly different. This is evidence that the causal treatment effect is very strong with the treatment being mandatory health insurance purchase.

The boxplot of total health expenses comparing baseline and endline supports the average treatment effect results since the endline median is less than the baseline median. The average treatment effect is calculated by the average of the endline minus the baseline. The sign of the average treatment effect is determined by the endline minus the baseline and since the endline is less than the baseline, the sign would be negative as in the result of the average treatment effect.

This is not a full explanation of the effect of the mandatory health insurance purchase. There are other predictors that could explain the effect of the mandatory health insurance purchase. Future research can include the investigation of the effect of mandatory health insurance purchase on other variables such as the total household consumption and the total hospital expenses. It is also possible to investigate different matching methods for estimating the average treatment effect.

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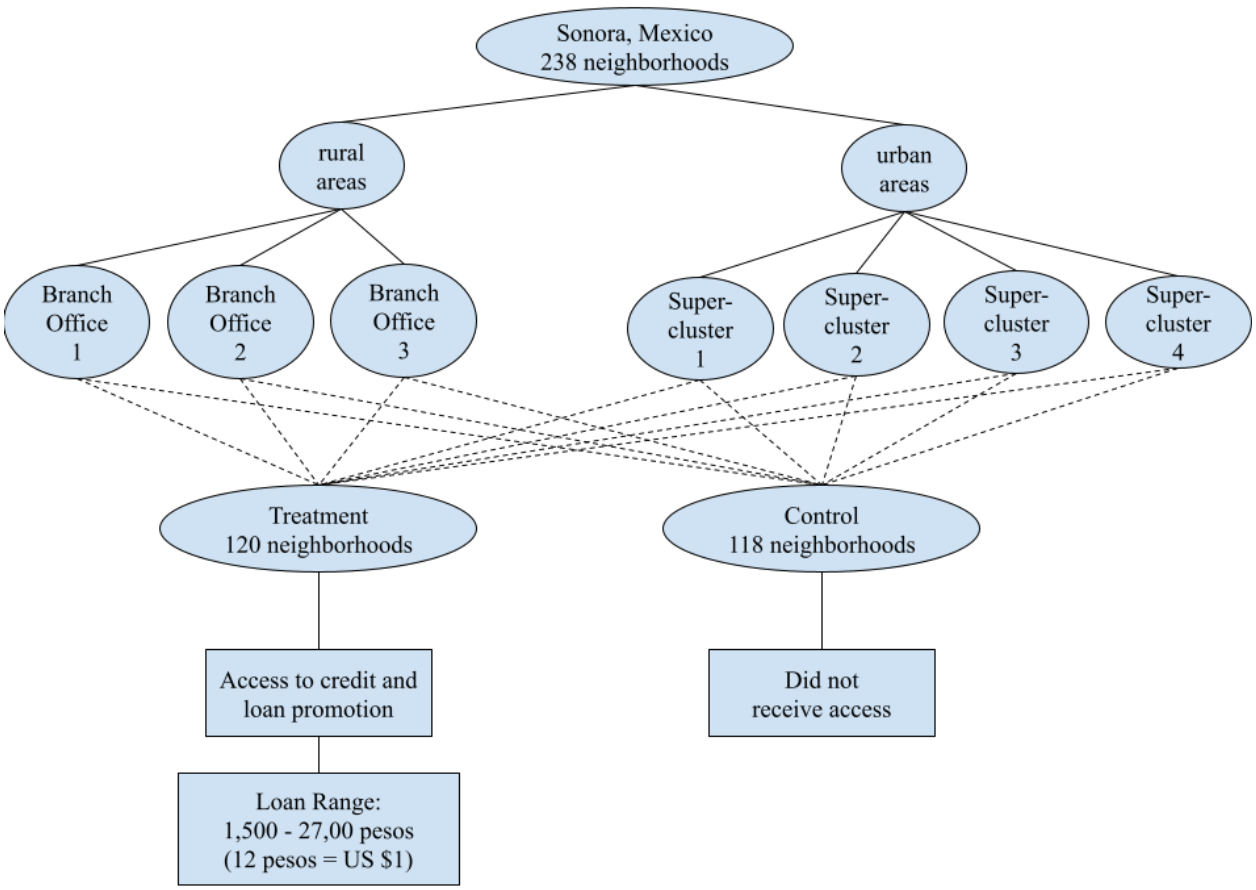
APPENDIX

**Figure 1.2** [6]

**Mexico Random Sampling**

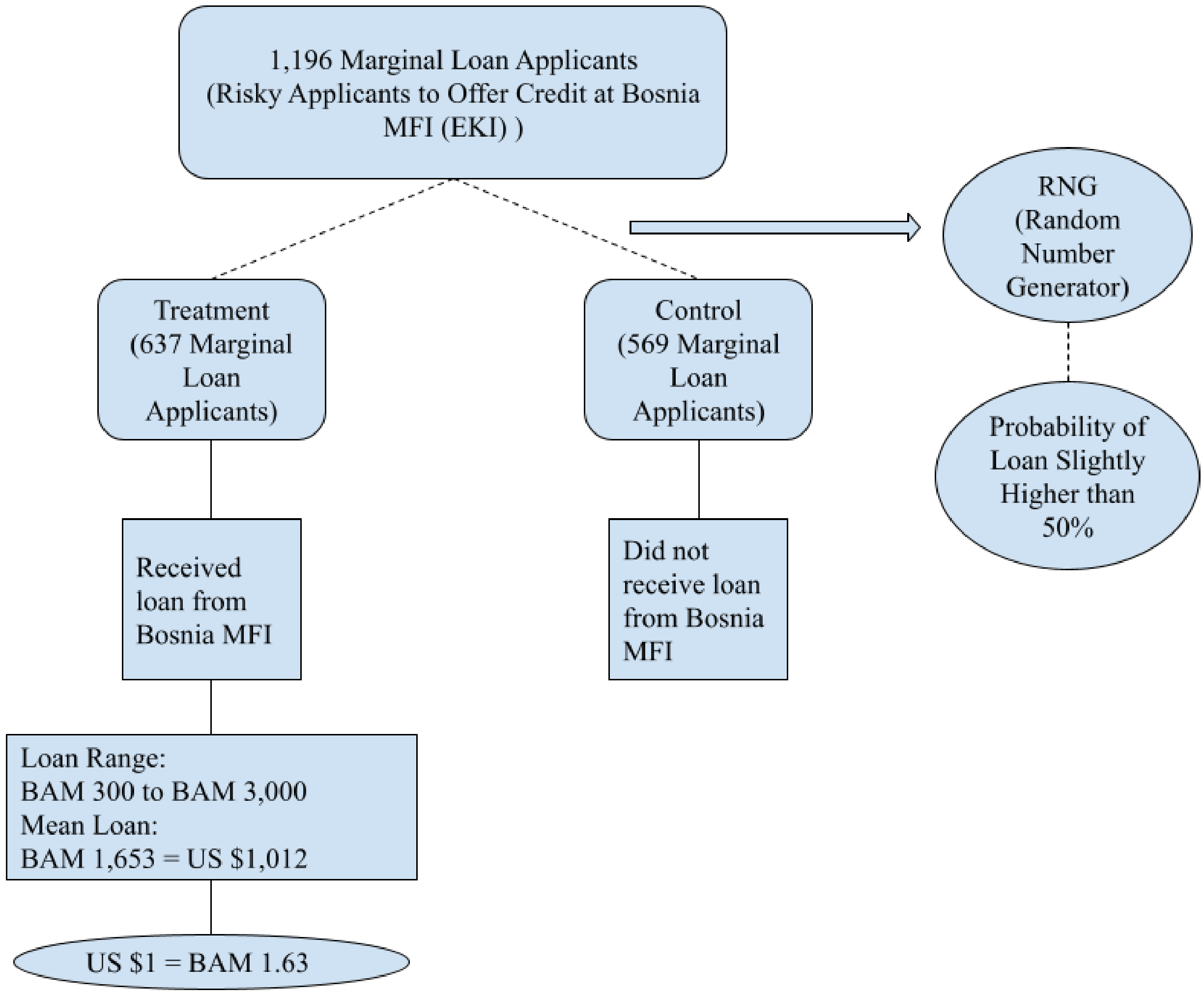



[6] The objective was to estimate the impacts on credit, self-employment, income, labor supply, expenditures, social, and other welfare at the community level from group lending expansion from Credito Mujer MFI in Mexico (Angelucci et al., 2015).

Sonora is a Mexican state. Neighborhoods were clustered by formal or informal neighborhood boundaries for urban areas and well-defined communities for rural areas. A first-time borrower loan was 1,500-6,000 pesos (US $125 - US $500). Larger loans were available to members of a group that had repaid prior loans (Angelucci et al., 2015).

**Figure 1.3** [7]

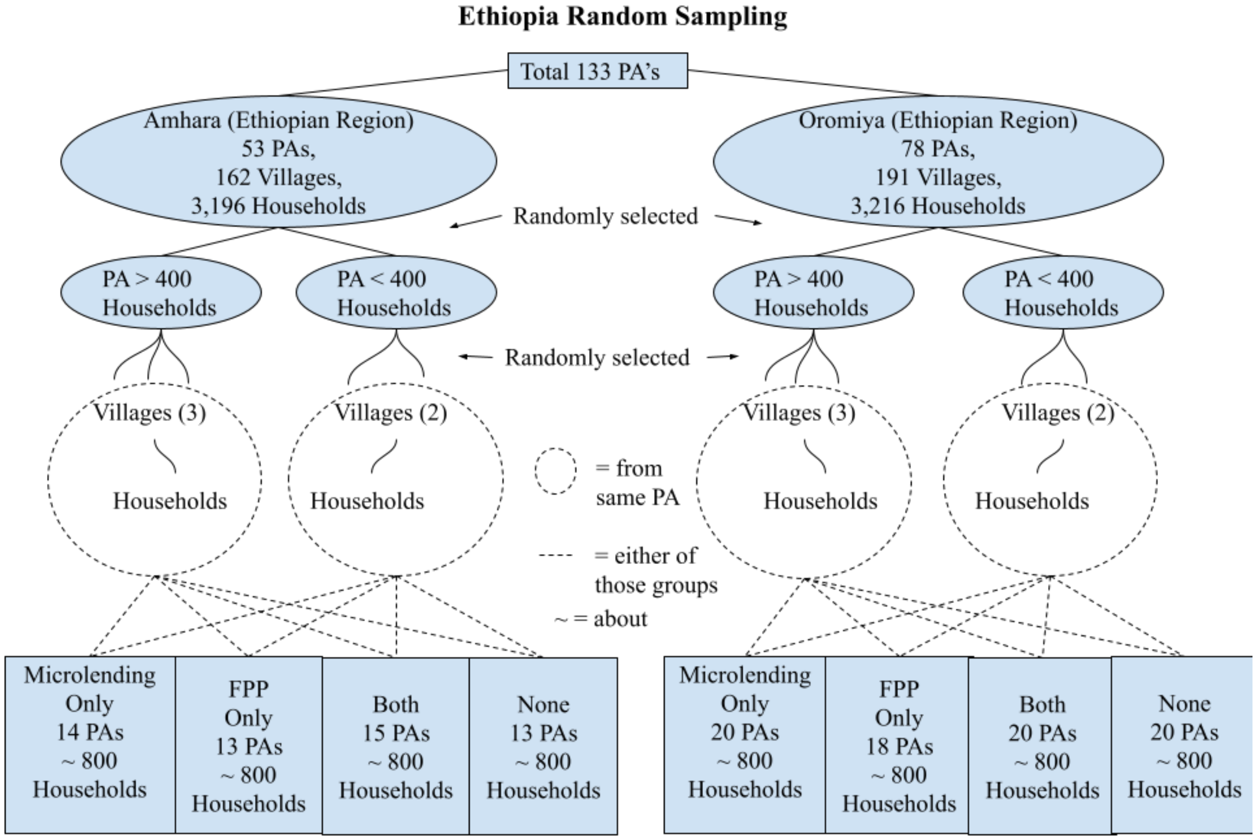
**Bosnia Random Sampling**




[7] The objective was to find evidence of treatment effect on social, consumption, savings, self-employment/income, hours worked, and intervention and access to liquidity from increased availability of microcredit from a Bosnia MFI (EKI) (Augsburg et al., 2015).

Risky was determined by individual screening by trained loan officers. Risky characteristics were young, less likely to be married, having less education, less likely to be employed full-time, and being poor. The sample participating branches were from the Federation of Bosnia and Herzegovina and Republika Srpska. The sample was for these 14 branches of Bosnia MFI. Bihac, Banjaluka, Biggino, Mostar, Visegrad, Boboj, Zenica, Sarajevo, Zivinice, Tuzla, Gradacac, Breko, Bjeljina, and Zvornik (Augsburg et al., 2015).

**Figure 1.4** [8]

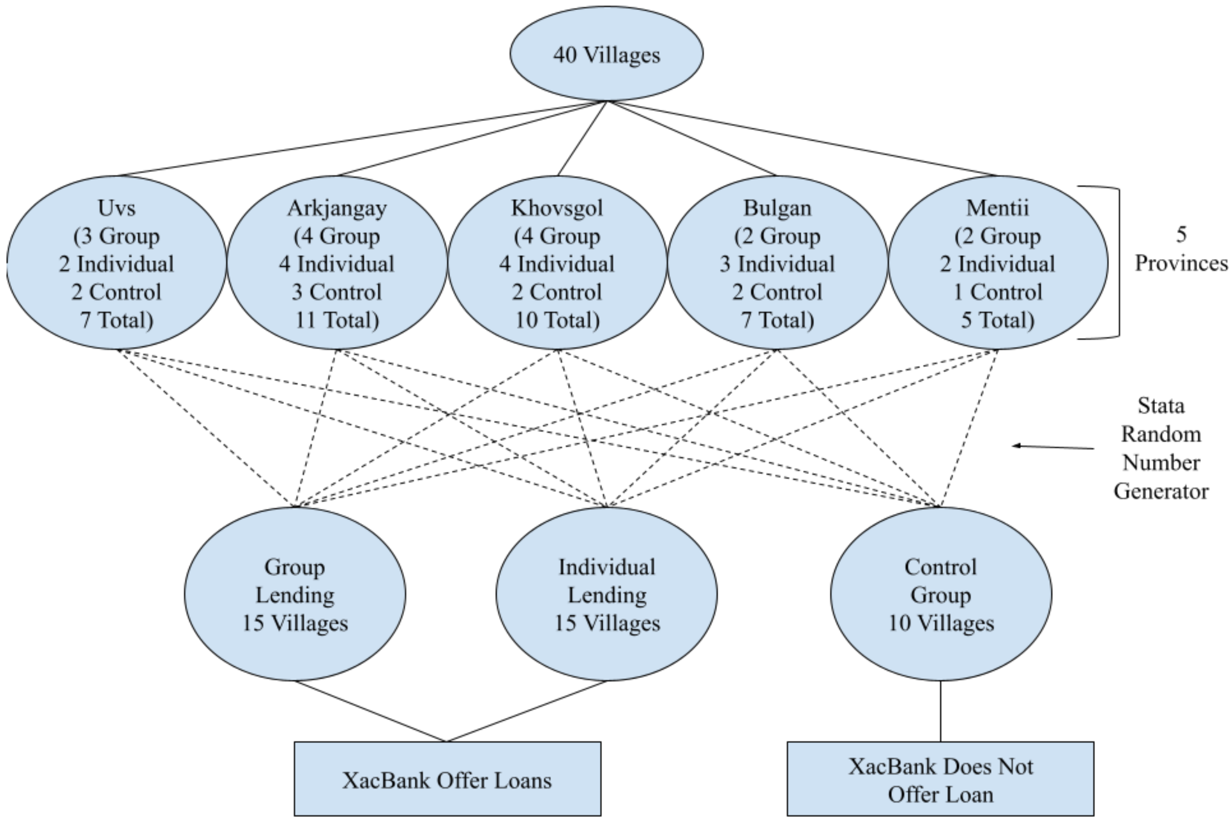



[8] The objective was to study the impact of borrowing behavior, household economic activity, and socioeconomic indicators from increased access to microfinance in rural Amhara and Oromiya, Ethiopia from 2003-2006 with a focus on whether combined microcredit with family planning services would increase contraceptive use (Tarozzi et al., 2015).

FPP stands for family planning program that provided information on family planning (and contraceptives to the FPP-only group). PA (Peasant Associations) are the smallest local unit of government in Ethiopia, containing a number of villages. All villages and households from the same PA were assigned to the same group for the sample. Randomization was performed independently in the 2 regions. Random assignment by PA was performed using statistical software by a biostatistician at Family Health International, North Carolina, U.S. (Tarozzi et al., 2015).

**Figure 1.5** [9]

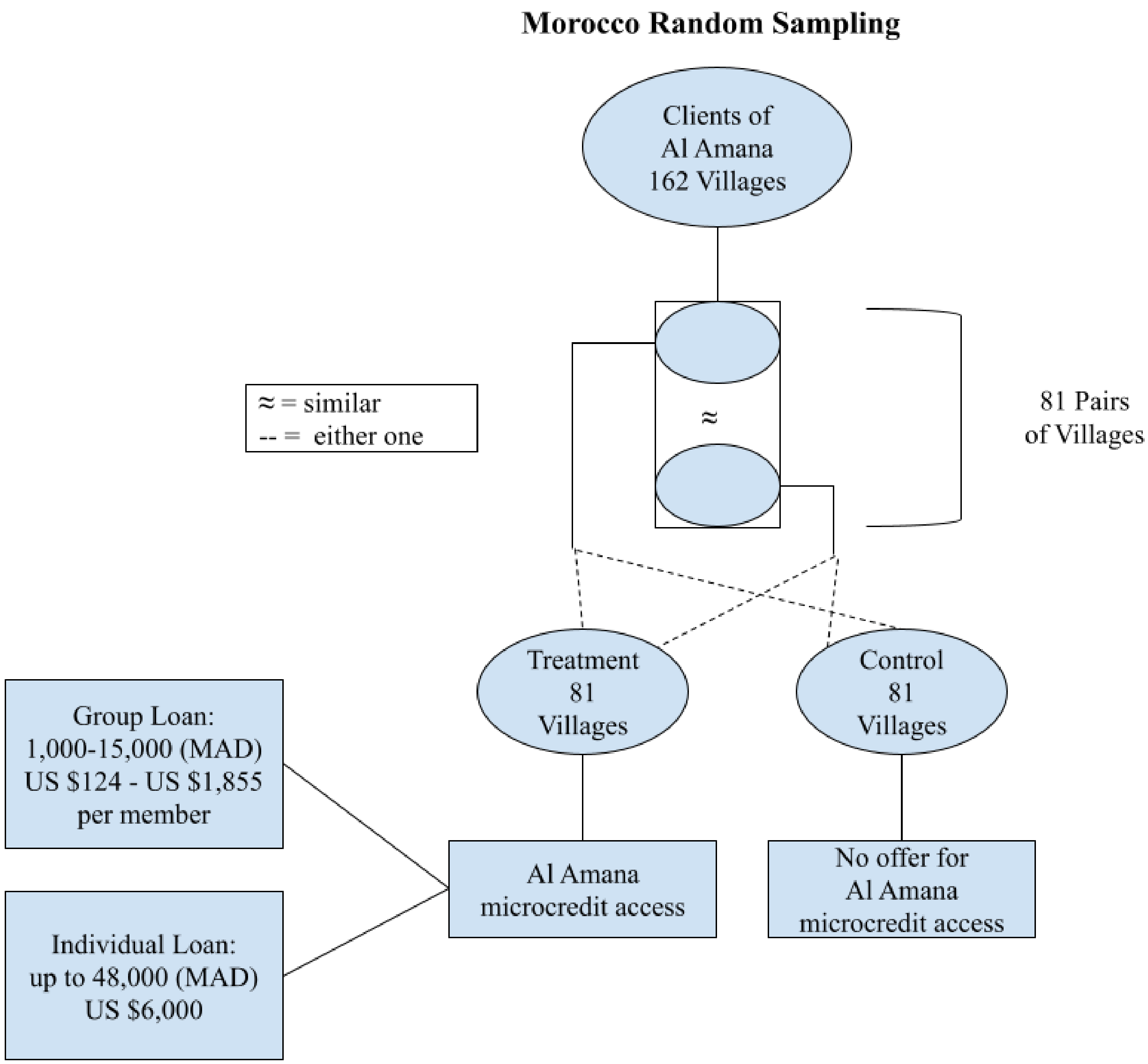
**Mongolia Random Sampling**




[9] The objective was to find evidence of the impact on credit, self-employment activities, hours worked, consumption, social, and income from the group and individual lending but mostly focused on the joint-liability microcredit program targeted at women in rural Mongolia (Attanasio et al., 2015).

1,148 poor women were from the forty villages in the study. Potential groups of seven to fifteen people were formed at the start of the study by the women. In many cases, actual groups differed from the potential groups. The maximum size of the first loan to a group member was MNT 500,000 (about $435). Individual loans were similar but larger on average than sub-loans to group members (Attanasio et al., 2015).

**Figure 1.6** [10]




[10] The objective was to find evidence of the impact of access to microfinance in remote rural areas in Morocco from Al Amana (MFI) on credit access, self-employment activities, income, time worked, consumption, education, and female empowerment (Crépen et al., 2015).

Villages were matched in pairs based on the number of members in the households, accessibility to the center of the community, existing infrastructure, type of activities in households, and type of agricultural activities. Al Amana (MFI) mainly offered group liability loans in rural areas. Groups were formed by three to four members. For the period of focus, households almost only took out group liability loans. Later, individual loans were offered for housing and nonagricultural business in rural areas with an additional set of requirements and targeted to clients that could provide collateral. There was a baseline sample of 4,465 households over 47 branches, 27 provinces, and 11 of the 16 regions in Morocco (Crépen et al., 2015).