**Alleviating Rural Poverty: The Role of Access to Finance**

**(A Household Level Analysis)**

## Abstract

# Introduction

Developments within poor countries have received a lot of attention in the world recently. Focus has constantly been drawn to the growing levels of poverty and inequality in developing countries. As a result, international organizations and governments of developed countries have partnered with governments and institutions in developing countries to aid in the eradication of poverty. More specifically, rural poverty has gained a great deal of attention in recent times. This mostly has been due to the rate of rural-urban migration, encouraged by the growing disparity in economic opportunities between rural and urban centers.

The financial system which comprises banks and other financial markets plays an important role in an economy. This includes resource pooling and allocation between savers and borrowers. A properly functioning financial system can be considered the heart of every economy because it becomes the key to investments and economic growth. Therefore, providing access to financial services is an important way to provide the necessary foundation for individuals to participate effectively in the economy. Making financial services readily available and affordable to households in disadvantaged areas is therefore mostly termed as financial inclusion (Danquah et al., 2017a). Leeladhar (2006) asserts that banking services should be considered a public good and hence improving access to everyone, especially the disadvantaged in the economy should be at the core of public policy, just like any other public good. This is because of the various benefits and positive externalities that banking services provide to such communities. Financial exclusion is not only costly but it is dangerous and could heavily impact growth and development. It increases the travel time required to access financial services and this hampers resource mobilization and allocation. It will affect rural communities’ access to credit facilities for investments, hampers the formalization of rural areas, and could also pose a security threat as holders of cash face high risks of getting robbed. Leeladhar (2006) summarizes the danger of financial exclusion in the statement that “Financial exclusion may well lead to social exclusion”. Financial inclusion is a key factor in the financial development of every country, hence the Millennium Development Goals (MDGs) and the much recent Sustainable Development Goals (SDGs) have stressed the need to enhance financial inclusion especially in rural areas.

Several papers have investigated the impact of access to finance on poverty across the world. While some authors limit the analysis to microfinance companies, other authors have extended the analysis to other broader forms of financial services. Some authors do not find a clear relationship between access to credit and poverty. For instance, Al Mamun et al. (2013) studied the correlation between microfinance and poverty in Bangladesh. They argue that though microfinance contributes significantly to the mobilization of savings, its impact on poverty is not clear. Bhandari (2009) also finds that access to financial services, measured by the number of people who have access to bank accounts, has no significant effect on poverty. They argue that developing a more inclusive financial system should be given priority in tackling poverty in rural areas.

A similar study conducted in China by Ho & Odhiambo (2011) using domestic credit to the private sector as a proxy for financial development. They find a bidirectional causal relationship between financial development and poverty reduction.

Using data from 1983 to 2005, Ayyagari et al (2013) study the impact of financial deepening on rural poverty in India. Using instrumental variable estimation techniques, they find that financial deepening and financial inclusion contribute to poverty alleviation by fostering rural entrepreneurship activities. Similarly, Geda et al. (2008) employ a household-level panel data from 1994 to 2000 to study access to finance and poverty in Ethiopia. Their findings show that access to finance is an important factor in consumption smoothening and poverty reduction. Reyes (n.d.) also studies access to finance and poverty in Bolivia. Their findings show that access to finance is an important factor in spurring economic growth and poverty reduction.

Dimova & Adebowale (2018) also study the effect of access to formal financial services on household welfare in Nigeria. Using household-level survey data, they find that access to finance improves household welfare. It, however, increases inter-household inequality and reduces the inequality gap between urban and rural centers. Danquah et al (2017) also study how access to financial services through rural community banks affects the poverty of rural households in Ghana. They utilize the sixth round of the Ghana Living Standards Survey, and by applying instrumental variable techniques, they find that the living standard of rural households is improved significantly by the presence of rural community banks.

Aliero & Ibrahim (2012) also study the role of access to finance in reducing rural poverty in Nigeria with a focus on rural areas in Katsina state. A cross-sectional survey data was utilized and multinomial logit techniques were employed. The findings suggest that access to financial services in rural areas reduces poverty. Quach (2005) studies the impact of access to finance on poverty in rural Vietnam. They also find that improving access to finance to rural areas reduces poverty and improves welfare.

Pitt & Khandker (1998) also employ quasi-experimental techniques to estimate the impact of group-based credit programs on poor households in Bangladesh. They find that the provision of credit to households increases household expenditures and reduces poverty. Roodman & Morduch (2014) in replicating the work of Pitt & Khandker (1998) found that the finding that microcredit reduces poverty disappears when outliers are dropped or when robust estimators are used.

Park & Mercado (2015) also study financial inclusion, poverty, and inequality for a sample of 37 Asian countries. They construct an index of financial inclusion and estimate its effect on poverty and inequality. They find that financial inclusion significantly reduces poverty and inequality.

Quach et al. (2005) also estimate the impact of access to credit on poverty for Vietnam using household surveys conducted in 1993 and 1998. They find that access to credit reduces poverty significantly. This finding holds irrespective of whether the households are more or better-off. Similarly, Duong & Nghiem (2014) estimated the effect of microcredit on poverty in Vietnam. They utilize the Vietnam Living Standards survey covering the period 1992-2010. They find that the provision of micro-loans significantly reduces poverty in Vietnam.

Establishing a causal relationship between access to finance and poverty is a major difficulty encountered by these studies. Endogeneity concerns fraught the analysis. Poverty levels may well determine if people are able to access financial services. This endogeneity concerns are ignored by authors such as Aliero & Ibrahim (2012) and Al Mamun et al. (2013), while authors such as Ayyagari et al.(2013) get around this by using instrumental variables. An obvious concern with using instrumental variables is finding a good instrument. Even more complicated is a situation where the endogenous access to finance is a binary variable. Geda et al. (2008) argues that when the endogenous variable is also a dummy variable, instrumental variable techniques become inappropriate. Danquah et al. (2017b) get around this by estimating a bivariate probit model that allows for correlation between the error term from participation equation and the error term from the outcome equation. This paper contributes to the literature by applying matching techniques to causal inference. Matching techniques have gained popularity in the causal inference literature in recent times but to the best of our knowledge, the only application of matching in techniques in this literature is by Arun et al. (2006) who apply propensity score matching techniques in a case study of microfinance and poverty in India. This paper contributes by employing matching techniques that are improvements on the propensity score techniques and provide superior results in terms of balance and robustness. We find a significant but weak positive relationship between access to finance and poverty reduction in rural communities in Ghana.

## Data and Variable Description

The paper employs a data set extracted from the 7th round of the Ghana Living Standards Survey (GLSS). The GLSS survey data was gathered between 2016 and 2017. It is a periodic household survey data that is collected to help assess the welfare of citizens. Since the focus of the paper is on rural access to financial services, the data consists of only respondents from rural communities in Ghana. The dataset consisting of 5673 respondents is extracted from the survey for this analysis. The sampling design is not random as disproportionately larger samples are drawn from regions with smaller populations. Weights that reflect the probability of each household getting selected are computed and used to capture the true contribution of each respondent to the sample[[1]](#footnote-1).

In the GLSS survey, the poverty status of individuals is categorized into three; very poor, poor, and non-poor. The dependent variable (not poor) is codded as a binary variable equal to one if a respondent is non-poor. Those categorized as very poor and poor are put together and are treated as the control group. Since the poor are the reference category, a positive coefficient will be interpreted as a decrease in the probability of being poor while a negative coefficient implies an increase in the probability of being poor. Access to finance is the main independent variable of interest and is codded as a dummy variable equal to 1 if respondents have a bank account or are contributing to a loan/savings scheme and zero otherwise. Other independent variables that are controlled for include the following:

* Age of the respondent measured in years.
* Level of education, categorized into primary, secondary, and tertiary. Those without any formal education are the reference category.
* Religious affiliation. Three dummy variables are specified to represent the three major religious affiliations in Ghana: Christianity, Islam, and Traditional. Those without religious affiliations are the control group.
* Marital status: A dummy variable is created for married with the unmarried being the reference category.
* Distance to the nearest bank. This is the measure of the distance from the community of a respondent to the nearest bank in kilometers. Other studies such as Danquah et al. (2017b) use this measure as an instrument for access to financial services.
* Labor force participation. A binary variable is used to capture a respondent’s participation in the labor force. It takes a value of 1 if the respondent is in the labor force and zero otherwise.
* Household size. The size of the household is measured as the number of people living in the respondent’s household.
* Log of total household income. Total household income is the sum of incomes that accrue to households from all sources including wage income.
* Employment status. A binary variable is used to capture the employment status of a respondent. It takes the value of one if the respondent is employed and zero otherwise.

## Empirical Methodology

In attempting to get close to establishing a causal relationship between access to finance and rural poverty, the concern majorly is that access to finance is not purely exogenous. The poverty status of respondents may well determine their ability to access financial services. This implies a possible reverse causation between poverty and access to financial services. It also suggests that access to finance is not purely random and may well be driven by some significant confounders. When such endogeneity exists, the use of ordinary regression techniques become inappropriate. The immediate solution is the use of instrumental variable techniques. The problem however is finding the appropriate instruments for access to finance. It is even more problematic especially when the endogenous access to finance measure is a dummy variable. Geda et al. (2008) argue that when the endogenous variable is a binary variable with a non-normal distribution, the instrumental variable technique may not be appropriate.

Matching techniques have become a popular technique used in reducing selection bias and obtaining balance on observable covariates ( Abadie & Imbens, 2006, Tsiboe et al., 2021). Unlike in purely randomized studies, comparing treatment and control groups in a nonrandomized study can be problematic as these two groups could differ significantly based on some observable characteristics. Matching techniques hence provide a way of generating a matched control group that is comparable to the treatment group based on observables. This allows outcomes between these two groups to be compared (Rosenbaum, 2005). Matching techniques avoid functional form issues as researchers are not required to make any functional form assumptions (Tsiboe et al., 2021) .

The most popular matching technique is the propensity score matching proposed by Rosenbaum & Rubin (1983). The technique involves matching treated units to control units using a propensity score difference as a distance measure. If the propensity score model is correctly specified, it asymptotically eliminates any bias due to confounders. Despite the popularity of this technique, King & Nielsen (2019) argue that propensity scores should not be used for matching. In their view, propensity score matching attempts to approximate a purely randomized experiment rather than a fully blocked random experiment which is more realistic. This will likely increase imbalances, inefficiency, model dependence and significant bias in estimates of the treatment effects using propensity scores. Propensity scores are also dependent on the specification of the right functional form. A mis-specified propensity score model could produce biased estimates (Drake (1993).

Given these problems with propensity score matching, we employ other innovative matching techniques. The nearest neighbor matching is one of the easiest techniques to implement. With this technique, each treatment observation is matched to an eligible observation in the control group that is closest to it based on a distance measure. The propensity score difference is the most common distance measure used. It is sometimes called greedy matching because each matched unit is done independently off how other pairs are matched. This implies that the quality of the matching depends on order in which the treated observations are matched. The method could also lead to poor matching especially for treated observations that do not have propensity scores similar to that of the control observations (Stuart, 2010).

Optimal matching offers an improvement on the nearest neighbor matching. This method takes into account all matches in choosing the best each for each treatment unit. It uses a global distance measure to match treatment units to control unites. Generally, matching distances are smaller compared to nearest neighbor matching especially when the number of control units are few. According to Gu & Rosenbaum (1993) , optimal matching does not do a good job at creating groups with good balance although it does a better job at assigning the controls to treatment units.

Full matching also offers an improvement on both optimal and nearest neighbor matching techniques. With full matching, matched sets are created which contain at least one treated observation or at least one control observation. These sets are generated in an optimal way such that treated observations with many similar comparison observations based on the propensity score are grouped with many comparison individuals and treated observations with less similar comparison observations are grouped with fewer comparison individuals. This allows for full utilization of all the data points while attaining balance (Stuart, 2010).

The last matching technique we employ is genetic matching. This method is advanced by Diamond & Sekhon (2013). Genetic matching is considered the most efficient matching technique so far. The basic idea is to match treated observations to control observations based on the smallest weighted Mahalanobis distances (MD). It uses a search algorithm developed by Mebane Jr & Sekhon (2011) to achieve covariate balance across treated and matched control groups. Other matching techniques use standard Mahalanobis distance methods. However, these methods fail especially when there are covariates with nonellipsodal distributions. The use of weighted Mahalanobis distances by genetic matching ensures that covariate balance can still be achieved even under nonellipsodal distributions (Sekhon & Grieve, 2012). The generalized Mahalanobis distance measure for two units *i* and *j* is stated by Diamond & Sekhon (2013) as:

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| --- | --- | --- |
|  |  | (1) |

Where *X* is a matrix of observed confounders, *S* is the covariance matrix of *X* and *XT* (The transpose of *X* ). *W* is a positive definite matrix of weights and is the Cholesky decomposition of *S.*

In this paper, we estimate and compare the treatment effects using the above stated matching techniques. We also compare the estimates from matching to he standard logit and probit estimations for robustness purposes.

## Model

In this paper treatment is assigned when a respondent has access to financial services. That is, a respondent is assigned treatment if he or she has a bank account or is contributing to a loan or savings scheme. The control group will be respondents who have no bank account or do not contribute to any loan of savings scheme. We define the treatment variable as *Accessi* which is a dummy variable equal to one if a respondent *I* receives treatment and zero otherwise. We define as the poverty status of respondent *i* who received treatment or has access to financial services and will be the poverty status of a respondent who is in the control group or does not have a bank account or contribute to any savings or loan scheme. We will let be a vector of the pretreatment covariates. We make the conditional ignorability or exchangeability assumption. That is, we assume that conditional or the observable pre-treatment covariates, the individuals’s potential poverty status is independent of his potential treatment assignment. This is states as:

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| --- | --- | --- |
|  |  | (2) |

This assumption implies that after controlling for all the observable covariates, the treatment assignment is approximately random. We have tried to control for most of the relevant observable confounders which could potentially affect access to finance. This is a strong assumption as it is practically impossible to control for every possible covariate that could potentially affect treatment. This means that this assumption is inherently untestable. However, we can test the extent to which our results depend on this assumption by conducting a sensitivity analysis which is espoused in detail in the next section.

We conduct the different matching techniques on the data to obtain a matched treated and control sample. Our goal will then be to estimate the average treatment effect on the treated (ATT). The estimate of the ATT is represented as:

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| --- | --- | --- |
|  |  | (3) |

Where is the estimated treatment effect of access to finance on our measure of poverty for individual *i.*

**Sensitivity Analysis.**

Our ATT estimates are valid only if there are no significant unobservable confounders. The presence of any unobserved confounders will bias our estimates. This situation is referred to as hidden bias. In observational data like these, pure randomization is generally not possible to attain. There is no practical way to control for every possible factor that potentially determines selection into the access to finance category. In other words, the ignorability or exchangeability assumption is not always valid in observational data. What is relevant to our analysis then is how sensitive our estimates are to the presence of an unobserved confounder. If the estimates are very sensitive to a possible confounder, it will imply that inferences from these estimates are not reliable. Rosenbaum (2002) developed a sensitivity analysis that can be used as a robustness check on our estimates. The framework acknowledges that it is practically impossible to avoid selection bias. Instead of testing for the presence of unobserved confounders, the test determines the degree to which our results hinge on the validity of the no confounders assumption (Becker & Caliendo, 2007).

Let's take two individuals *i* and *q* respectively from our sample. Each has a probability *ρi* and *ρq*  of receiving treatment, in this case, getting access to finance. We define an unobserved covariate *wi*. The odds of individual *i*  receiving getting access to finance is given by and the that of individual *q* is . This implies that the odds-ratio can be expressed as:

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| --- | --- | --- |
|  |  | (4) |

If we assume a logistic distribution, this odds ratio can be written as:

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| --- | --- | --- |
|  |  | (5) |

If individuals are identical in terms of the observed covariates *X,* then equation 5 reduces to:

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| --- | --- | --- |
|  |  | (6) |

From equation 6, we see that when the two individuals are no different with respect to the unobservable factor *w,* then the odds ratio is 1 and each individual has an equal chance of getting access to finance. This is also true ifthe difference based on unobservables is not significant (. Otherwise, the odds ratio will be different from one, which will imply that one individual has a greater or lesser chance of getting access to finance compared to another.

Rosenbaum (2002) develops upper and lower bounds p-values which can be used to test for different values of the odds ratio.

|  |  |  |
| --- | --- | --- |
|  |  | (7) |

Where . The larger the value of *Г,* the higher the odds that our estimates will change due to the magnitude of the unobserved confounder. For example, when it means that given that the two individuals have the same values of X, they differ in their odds of getting access to finance by a factor of 2. Since increases with hidden bias, we will simply test different values of to determine the level of bias that our estimates are sensitive to. Keele (2010) argues that given the difficulty in attaining randomness, research in social science is not robust to large values of . It is suggested that values between 1 and 2 should be used in social science research, hence in our estimation, we will do the sensitivity analysis for the range 1≤≤2.

Nearest neighbor matching

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Variable | Before Matching | | | After Matching | | | Bias Percentage Reduction |
| b | Mean (Treated) | Mean (Control) | SMD | Mean (Treated) | Mean (Control) | SMD |  |
| Demographic Characteristics |  |  |  |  |  |  |  |
| Gender (Male=1, Female =0) | 0.7637 | 0.7317 | 0.0753 | 0.7637 | 0.7446 | 0.0450 | 40.2 |
| Age (in years) | 44.5067 | 49.1563 | -0.3167 | 44.5067 | 45.5481 | -0.0709 | 77.6 |
| Primary | 0.2410 | 0.2748 | -0.0792 | 0.2410 | 0.3185 | -0.1814 | -129.1 |
| Secondary | 0.3790 | 0.2014 | 0.3661 | 0.3790 | 0.3557 | 0.0480 | 86.9 |
| Tertiary | 0.1355 | 0.0101 | 0.3665 | 0.1355 | 0.0191 | 0.3399 | 7.2 |
| Married | 0.6303 | 0.6037 | 0.0551 | 0.6303 | 0.6107 | 0.0407 | 26.1 |
| Christian | 0.7187 | 0.5559 | 0.3622 | 0.7187 | 0.6613 | 0.1276 | 64.8 |
| Islam | 0.1520 | 0.1767 | -0.0687 | 0.1520 | 0.1639 | -0.0331 | 51.8 |
| Traditional | 0.0801 | 0.1729 | -0.3415 | 0.0801 | 0.1075 | -0.1009 | 70.4 |
| Household size | 4.8568 | 4.9350 | -0.0247 | 4.8568 | 4.9100 | -0.0170 | 32.0 |
| Labor Market Status |  |  |  |  |  |  |  |
| Labor force participation (Yes=1, No=0) | 0.9395 | 0.8502 | 0.3745 | 0.9395 | 0.9302 | 0.0390 | 89.6 |
| Employment status (Employed=1 Unemployed =0) | 0.8899 | 0.7633 | 0.4044 | 0.8899 | 0.8744 | 0.0495 | 87.7 |
|  |  |  |  |  |  |  |  |
| Log of household total gross income | 8.9671 | 8.0527 | 0.6096 | 8.9671 | 8.6567 | 0.2070 | 66.1 |
| Distance to the nearest (In kilometers) | 12.2754 | 15.5358 | -0.2456 | 12.2754 | 13.1748 | -0.0678 | 72.4 |
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Full matching

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| --- | --- | --- | --- | --- | --- | --- | --- |
| Variable | Before Matching | | | After Matching | | | Percent Balance Improvement |
|  | Mean (Treated) | Mean (Control) | SMD | Mean (Treated) | Mean (Control) | SMD |  |
| Demographic Characteristics |  |  |  |  |  |  |  |
| Gender (Male=1, Female =0) | 0.7637 | 0.7317 | 0.0753 | 0.7637 | 0.7446 | 0.0016 | 97.9 |
| Age (in years) | 44.5067 | 49.1563 | -0.3167 | 44.5067 | 44.0404 | -0.0070 | 97.8 |
| Primary | 0.2410 | 0.2748 | -0.0792 | 0.2410 | 0.2179 | 0.0539 | 31.9 |
| Secondary | 0.3790 | 0.2014 | 0.3661 | 0.3790 | 0.3641 | 0.0307 | 91.6 |
| Tertiary | 0.1355 | 0.0101 | 0.3665 | 0.1355 | 0.1499 | -0.0421 | 88.5 |
| Married | 0.6303 | 0.6037 | 0.0551 | 0.6303 | 0.6521 | 0.0451 | 18.1 |
| Christian | 0.7187 | 0.5559 | 0.3622 | 0.7187 | 0.6879 | 0.0685 | 81.1 |
| Islam | 0.1520 | 0.1767 | -0.0687 | 0.1520 | 0.1822 | -0.0842 | -22.6 |
| Traditional | 0.0801 | 0.1729 | -0.3415 | 0.0801 | 0.0873 | -0.0263 | 92.3 |
| Household size | 4.8568 | 4.9350 | -0.0247 | 4.8568 | 5.1429 | -0.0911 | -265.6 |
| Labor Market Status |  |  |  |  |  |  |  |
| Labor force participation (Yes=1, No=0) | 0.9395 | 0.8502 | 0.3745 | 0.9395 | 0.9340 | 0.0233 | 93.8 |
| Employment status (Employed=1 Unemployed =0) | 0.8899 | 0.7633 | 0.4044 | 0.8899 | 0.8810 | 0.0283 | 93.0 |
|  |  |  |  |  |  |  |  |
| Log of household total gross income | 8.9671 | 8.0527 | 0.6096 | 8.9671 | 8.8617 | 0.0703 | 88.5 |
| Distance to the nearest (In kilometers) | 12.2754 | 15.5358 | -0.2456 | 12.2754 | 12.0158 | 0.0196 | 92.0 |
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Optimal Matching

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| --- | --- | --- | --- | --- | --- | --- | --- |
| Variable | Before Matching | | | After Matching | | | Percent Balance Improvement |
|  | Mean (Treated) | Mean (Control) | SMD | Mean (Treated) | Mean (Control) | SMD |  |
| Demographic Characteristics |  |  |  |  |  |  |  |
| Gender (Male=1, Female =0) | 0.7637 | 0.7317 | 0.0753 | 0.7637 | 0.7653 | -0.0037 | 95.1 |
| Age (in years) | 44.5067 | 49.1563 | -0.3167 | 44.5067 | 44.4364 | -0.0633 | 80.0 |
| Primary | 0.2410 | 0.2748 | -0.0792 | 0.2410 | 0.2958 | -0.1282 | -61.9 |
| Secondary | 0.3790 | 0.2014 | 0.3661 | 0.3790 | 0.3490 | 0.0618 | 83.1 |
| Tertiary | 0.1355 | 0.0101 | 0.3665 | 0.1355 | 0.0191 | 0.3399 | 7.2 |
| Married | 0.6303 | 0.6037 | 0.0551 | 0.6303 | 0.6474 | -0.0353 | 35.9 |
| Christian | 0.7187 | 0.5559 | 0.3622 | 0.7187 | 0.6634 | 0.1230 | 66.0 |
| Islam | 0.1520 | 0.1767 | -0.0687 | 0.1520 | 0.1779 | -0.0720 | -4.8 |
| Traditional | 0.0801 | 0.1729 | -0.3415 | 0.0801 | 0.1096 | -0.1085 | 68.2 |
| Household size | 4.8568 | 4.9350 | -0.0247 | 4.8568 | 5.0610 | -0.0650 | -161.0 |
| Labor Market Status |  |  |  |  |  |  |  |
| Labor force participation (Yes=1, No=0) | 0.9395 | 0.8502 | 0.3745 | 0.9395 | 0.9219 | 0.0737 | 80.3 |
| Employment status (Employed=1 Unemployed =0) | 0.8899 | 0.7633 | 0.4044 | 0.8899 | 0.8599 | 0.0958 | 76.3 |
|  |  |  |  |  |  |  |  |
| Log of household total gross income | 8.9671 | 8.0527 | 0.6096 | 8.9671 | 8.6123 | 0.2366 | 61.2 |
| Distance to the nearest (In kilometers) | 12.2754 | 15.5358 | -0.2456 | 12.2754 | 13.1342 | -0.0647 | 73.7 |
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| --- | --- | --- | --- | --- | --- | --- | --- |
| Variable | Before Matching | | | After Matching | | | Percent Balance Improvement |
|  | Mean (Treated) | Mean (Control) | SMD | Mean (Treated) | Mean (Control) | SMD |  |
| Demographic Characteristics |  |  |  |  |  |  |  |
| Gender (Male=1, Female =0) | 0.7544 | 0.6931 | 0.1424 | 0.7544 | 0.7288 | 0.0592 | 58.3 |
| Age (in years) | 44.4101 | 48.5783 | -0.2892 | 44.4101 | 46.209 | -0.1243 | 57.0 |
| Primary | 0.2300 | 0.3182 | -0.2094 | 0.2300 | 0.2914 | -0.1459 | 30.3 |
| Secondary | 0.4524 | 0.2577 | 0.3912 | 0.4524 | 0.3791 | 0.1472 | 62.4 |
| Tertiary | 0.1385 | 0.0094 | 0.3736 | 0.1385 | 0.0147 | 0.3583 | 4.1 |
| Married | 0.5937 | 0.5414 | 0.1065 | 0.5937 | 0.5465 | 0.0960 | 9.8 |
| Christian | 0.8025 | 0.6128 | 0.4764 | 0.8025 | 0.7399 | 0.1571 | 67.0 |
| Islam | 0.1107 | 0.1532 | -0.1353 | 0.1107 | 0.1225 | -0.0375 | 72.3 |
| Traditional | 0.0400 | 0.1216 | -0.4163 | 0.0400 | 0.0505 | -0.0533 | 87.2 |
| Household size | 4.4752 | 4.5836 | -0.0372 | 4.4752 | 4.4623 | -0.0048 | 88.1 |
| Labor Market Status |  |  |  |  |  |  |  |
| Labor force participation (Yes=1, No=0) | 0.9492 | 0.8820 | 0.3059 | 0.9492 | 0.9426 | 0.0300 | 90.2 |
| Employment status (Employed=1 Unemployed =0) | 0.9178 | 0.8132 | 0.3808 | 0.9178 | 0.8983 | 0.0710 | 81.3 |
|  |  |  |  |  |  |  |  |
| Log of household total gross income | 9.0084 | 8.1776 | 0.5394 | 9.0084 | 8.5317 | 0.3095 | 42.6 |
| Distance to the nearest (In kilometers) | 13.3852 | 14.3327 | -0.0667 | 13.3852 | 12.7968 | 0.0414 | 37.9 |
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ATT

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| --- | --- | --- | --- | --- | --- |
| Poverty measure | Probit Model (AME) | Nearest Neighbor Matching. (ATT) | Full Matching. (ATT) | Optimal Matching. (ATT) | Genetic Matching (ATT) |
| Not Poor (Yes =1, No = 0) | 0.1016\*\*\* | 0.0835534\*\*\* | 0.0920412\*\*\* | 0.0787702\*\*\* | 0.0819500\*\*\* |
|  | (0.0006) | (0.0124961) | (0.0117036) | (0.0122943) | (0.0127089) |
| Number of Matched treated |  | 1934 | 1934 | 1934 | 1934 |
| Number of Matched Control |  | 1934 | 3679 | 1934 | 1934 |
| Total sample | 5613 | 5613 | 5613 | 5613 | 5613 |

1. For details on how the weights are computed, check: https://open.africa/dataset/ghana-living-standards-survey-glss-7-2017/resource/839a1758-146c-40cd-957d-37d26aa84fb6 [↑](#footnote-ref-1)