Klover International Journal Economics and Business Administration
Volume 10, Issue 1, January-March 2022
ISSN: 2995-4258
Impact Factor: 7.30
https://kloverjournals.org/journals/index.php/eba

THE RELATIONSHIP BETWEEN FINANCIAL EXCLUSION AND POVERTY ALLEVIATION IN BENIN

Timothy, P. O.

Abstract

This study aims to analyze the relationship between financial exclusion and poverty reduction in Benin. The study uses data from the World Bank's Global Findex database for the years 2011, 2014, and 2017, and employs a probit model to determine factors contributing to financial exclusion, including lack of documentation, expensive financial services, distance from financial institutions, and lack of trust in financial institutions. The study also explores how individual characteristics such as age, education level, religion, gender, and employment status are associated with financial exclusion.

The findings of the study reveal a positive and significant impact of financial exclusion on poverty and demonstrate that access to financial services can contribute to poverty reduction by providing entrepreneurial opportunities and reducing barriers to economic transactions. Additionally, the study provides a composite measure of financial inclusion and computes a financial exclusion index to assess its impact on poverty. The results suggest that despite recent improvements in access to financial services in rural areas of Benin, access to formal financial institutions remains a challenge for vulnerable groups and small- and medium-sized enterprises.

This paper contributes to the literature on the impact of financial inclusion on poverty in Africa by investigating the effect of financial exclusion on poverty in Benin. The study emphasizes the importance of promoting financial inclusion and reducing financial exclusion as a means of reducing poverty in Benin and in similar developing countries.

Keywords: Financial exclusion, poverty reduction, Benin, Global Findex database, probit model, individual characteristics

1. Introduction

Poverty reduction has been the principal focus of the development agenda. In fact, for the past twenty years, countries have striven to achieve the first of the Sustainable Development Goals (SDGs) of eradicating extreme poverty, measured as people living on less than $1.25 a day, by 2030. Alongside microfinance, financial inclusion has been widely discussed in the theoretical and empirical literature as a successful strategy for poverty alleviation. According to the World Bank Group, "Financial inclusion means that individuals and businesses have access to useful and affordable financial products and services that meet their needs – transactions, payments, savings, credit, and insurance – delivered in a responsible and sustainable way". The theoretical link between financial inclusion and poverty is embedded in the financial development framework. There are direct and indirect channels through which financial inclusion affects poverty. In direct channels, financial inclusion contributes to poverty alleviation by enhancing entrepreneurial possibilities via access to credit, generating income, and better livelihoods. In indirect channels, by facilitating and stimulating economic transactions, financial inclusion boosts economic growth, which implies the creation of jobs and an increase in the government tax income that benefits the poor through employment and public spending on social programs (Anthony, Hadrat, George, Kwasi, & Samuel, 2021). Both direct and indirect channels have been documented in the empirical literature (Aportela, 1999; Bruhn & Love, 2014; Demirgüç-Kunt & Singer, 2017; Djossou, Monwanou, & Novignon, 2016; Dupas & Robinson, 2010; Zhang & Posso, 2017).

Despite a sustained increase in real gross domestic product (GDP) per capita over the past 20 years, more than 40% of the Beninese population was still living in poverty in 2015. For this reason, and the high penetration rate of smartphones in the country, the Beninese government has identified improving financial inclusion through digitalization as a successful strategy for poverty alleviation. Examples of various completed and ongoing initiatives in the country include the Digital Economy project (2019–2020) supported by the Embassy of the Netherlands, a large-scale randomized controlled trial assessing the performance of a Personal Finance Management mobile app. In addition, in 2020, the government of Benin created a financial services quality observatory with the aim of increasing the use of formal financial services by firms and individuals.

The number of bank branches has been recently increasing in rural areas of Benin, but despite this improvement, only 17% of the population had a bank account in 2015, and access to finance is difficult for some vulnerable groups and small- and medium-sized enterprises (Fund, 2018). The microfinance sector plays an important role in the country by financing the sectors of the economy and rural populations that are underserved by banks. Djossou et al. (2016) examined the impact of Benin's National Microcredit Program on poverty and found a positive and significant impact of individuals who had access to a microcredit program relative to those who did not. Dahoun et al. (2013) showed that microcredit has a positive impact on women's empowerment in Benin, especially on those who are heads of their household. Sylli (2012) showed that microcredit contributes to the living conditions of beneficiaries and helps to reduce poverty with more medium-term and long-term credit for agricultural activities in Benin. Although the existing literature summarized above has documented the positive effect of microfinance on individual welfare in Benin, several questions remain unanswered. These questions include: What are the main factors associated with the lack of financial inclusion (financial exclusion) in Benin, and how is financial exclusion associated with poverty in Benin? By answering these questions, the aim of our paper is to fill this gap in the literature and provide a better understanding of the relationship between poverty and financial inclusion in Benin.

Financial inclusion is a broad concept that includes several aspects of financial services. Most studies have looked for an appropriate measure of financial inclusion at the individual, household, and country levels (Gupte, Venkataramani, & Gupta, 2012; Park & Mercado, 2015; Sarma, 2008; Zhang & Posso, 2017). This study provides a composite measure of financial exclusion and assesses the extent to which it affects poverty using the Beninese Global Findex survey data. Specifically, we measure financial exclusion by computing a composite index considering several dimensions, such as account ownership, credit access, savings, financial resilience, financial account use, and online transactions. In the empirical literature on financial inclusion in Africa, many authors have used multiple indicators (use and ownership of an account, use of the account to save, and frequency use of the account, etc.) to capture the multidimensional nature of financial inclusion (Efobi, Beecroft, and Osabuohien (2014); Allen, Demirguc-Kunt, Klapper, and Peria (2016); Mohammed, Mensah, and Gyeke-Dako (2017); Tita and Aziakpono (2017)). Additionally, the study analyzes the determinants of financial exclusion by introducing factors of financial exclusion related to the various constraints faced by unbanked individuals (people who do not have accounts at formal financial institutions).

Timothy (2019) used a panel data analysis and macrolevel data for 36 African countries to show that financial inclusion, measured by the number of depositors with commercial banks, is positively correlated with life expectation. Using time series analysis and macroeconomic data, Afolabi (2020) found that financial inclusion, measured by rural loans, the number of bank branches and the level of liquidity, has a positive and significant effect on Nigeria's economic growth in the short and long runs. Demirgüç-Kunt and Klapper (2012) provided a descriptive statistical analysis of the measurement of financial inclusion in African countries, while Efobi et al. (2014) and Mohammed et al. (2017) used Global Findex data to study the determinants of financial inclusion in Sub-Saharan Africa. However, due to the heterogeneity of the financial sector in African countries, the findings of these studies cannot be applied to the Beninese context. Our study extends this literature by analyzing the causal impact of financial exclusion on poverty in Benin using microlevel data.

2. Data and Methodology

The data used in this study is from three rounds (2011, 2014, and 2017) of Benin's Global Findex microdata collected by the World Bank. In Benin, this survey was carried out face-to-face with 1000 interviewers aged 15 and above in the Bariba, Fon, French, and Anago languages.

2.1. Measure of Poverty and Financial Exclusion

2.1.1. Poverty

We measured poverty using the individuals' income quintiles that have been widely used in the literature (see Dollar and Kraay (2002) and Mohammed et al. (2017)). We used income quintile information because it is the only variable in the data that provides an ordered measure of individual welfare. We used the first- and second-income quintile as a proxy for poverty to account for the actual poverty rate in Benin, which was 40.1% in 2015 (Du Volet & Du Temps, 2015).

Table 1. Definition of the dimensions of financial inclusion (for the 2014 and 2017 databases).

Dimension (Weight)	**Indicator (Weight)**	**Measurement = 1 if... and zero otherwise**
Account ownership 1/6	Formal savings account 1/6	The individual has account at a formal financial institution (FI)
Account use 1/6	Deposit 1/12	The individual made a deposit in the past 12 months in a formal FI
	Withdrawal 1/12	The individual has withdrawn money in the past 12 months from a formal FI
Financial resilience 1/6	Emergency funds 1/6	The individual is able to come up with 1/20 of the GNI per capita in local currency within the next month
Savings 1/6	Business/Farm 1/18	The individual saved for a business/farm purpose in the past 12 months
	Old age 1/18	The individual saved for old age in the past 12 months
	Saved at a financial institution 1/18	The individual saved at a formal FI in the past 12 months
Credits 1/6	Loan for apartment 1/24	The individual took out a loan from an FI to purchase a home, apartment or land

	Medical borrowing 1/24	The individual borrowed for health or medical purposes in the past 12 months
	Business borrowing 1/24	The individual borrowed for business/farm purposes in the past 12 months
	FI borrowing 1/24	The individual borrowed from a bank or another formal FI in the past 12 months
Online transactions 1/6	Bill payment (only for 2017) 1/18	The individual made a bill payment online using the internet in the past 12 months
	Bought online (only for 2017) 1/18	The individual bought something online using the internet in the past 12 months
	Paid online 1/18	The individual paid for goods for delivery online or in cash in the past 12 months

Table 2. Definition of the dimensions of financial inclusion (2011).

Dimension (Weight)	**Indicator (Weight)**	**Measurement = 1 if… and zero otherwise**
Account ownership 1/6	Formal savings account 1/6	The individual has an account at a formal financial institution (FI)
Account use 1/6	Debit card 1/24	The individual has a debit card
	Credit card 1/24	The individual has a credit card
	Received wages 1/24	The individual received wages in the past 12 months using an FI account
	Gov. transfer 1/24	The individual received a gov. transfer using a formal FI account
Insurance 1/6	Insurance use 1/6	The individual has personal health insurance
Savings 1/6	Emergency 1/18	The individual saved for emergency purposes in the past 12 months
	Future expenses 1/18	The individual saved for future expenses in the past 12 months
	Saved at a financial institution 1/18	The individual saved at a formal FI in the past 12 months
Credits 1/6	Loan for apartment 1/12	The individual took out a loan from an FI to purchase a home, apartment or land

Klover International Journal Economics and Business Administration
Volume 10, Issue 1, January-March 2022
ISSN: 2995-4258
Impact Factor: 7.30
https://kloverjournals.org/journals/index.php/eba

	FI borrowing 1/12	The individual borrowed from a bank or another formal FI in the past 12 months
Online transactions 1/6	Bill payment 1/6	The individual made a bill payment online in the past 12 months

2.1.2. Financial Exclusion

Financial inclusion is measured in this study using six dimensions (account ownership, credit access, savings, financial resilience/insurance, financial account use, and online transactions). We computed the financial inclusion index by assigning equal weight to all dimensions of financial inclusion following Alkire and Santos (2014). For each dimension, we assigned the weight of 1/6 and equal weights within each dimension (see Table 1 & Table 2), and the index is obtained as a weighted sum of the dimensions' scores. Since we are interested in the financial deprivation aspect, the financial exclusion measure is defined as a dummy variable equal to 1 if the financial inclusion index is lower or equal to 1/6 (the individual, in this case, is financially excluded) and equal to 0 if the financial index is higher than 1/6 (the individual or household, in this case, is financially included). The cut-off of 1/6 is chosen to account for the usage of at least financial service.

2.2. Models and Empirical Strategy

The main objective of this study is to examine the potential impact of financial exclusion on poverty in Benin.

2.2.1. Model Specification

To meet this objective, we employed the simple probit model of the regression of financial exclusion on poverty. Equation 1 presents the likelihood of how being financially excluded is associated with poverty (where the first and second quintiles of poverty are used as a proxies).

$$Pov^*_{it} = \beta_0 + X'_{it}\beta + FE_{it}\delta + \mu_i \qquad (1)$$

Where $Povi = 1$ if $Pov^*_i > 0$ and $Povi = 0$ if $Pov^*_i \leq 0$ $t = 2017, 2014, 2011$ (the round of data); $Povi$ denotes the 20% poorest income quintile. This is a dummy variable
equal to 1 for the 20% income quintile and 0 otherwise.

X is a vector of individual characteristics; FE is the measure of financial exclusion; βo, β and δ are the parameters to estimate; and μi is the normally distributed error term capturing the unobserved factors.

2.2.2. Treatment Effects Model

The above defined model specification (Equation 1) does not allow for the assessment of the effect of financial services on poverty. The binary financial exclusion can be driven by endogeneity and sample selection bias since other individual unobservable attributes may exist that contain error terms, which bring the person to self-select him/herself as financially excluded or not. This problem induces financial exclusion (*FE)* to be correlated with the error term and causes a biased result. According to Imai and Arun (2008) and Imai, Arun, and Annim (2010), sample selection bias may arise in the financial market from two key problems. First, self-selection where the individuals/households choose whether or not to participate in a financial inclusion program based on observable or unobservable individual attributes. The second is an endogenous program placement where formal financial institutions may decide to select a certain group or category of people or areas (such as urban areas, rich or moderately poor people) to offer them formal financial services. Knowing that this problem could happen to our binary treatment variable, the result obtained by applying the simple ordinary least squares (OLS) or probit models cannot be interpreted as the causal effect. Therefore, the Heckman sample selection

Klover International Journal Economics and Business Administration
Volume 10, Issue 1, January-March 2022
ISSN: 2995-4258
Impact Factor: 7.30
https://kloverjournals.org/journals/index.php/eba

model (Heckman, 1979), which can be used to correct for sample selection bias or endogeneity associated with individuals' access to financial services, was employed in this study. Following Imai and Arun (2008); Imai et al. (2010); and Mohammed et al. (2017), we employed the treatment effects version of the Heckman sample selection model. This treatment effects model uses the Inverse Mills Ratio (IMR) to control for sample selection bias in a two-stage estimation procedure. In the first stage, the endogenous binary treatment (financial exclusion) is estimated by a probit model. The IMR is computed from the predicted values of the estimation of the probit model and reflects the degree of sample selection bias. In the second stage, the IMR calculated is included in the regression of the poverty index on various household characteristics and the financial exclusion variable. The baseline assumption is that the error term in the probit model and the error term in the main regression of poverty on financial inclusion are correlated and normally distributed. The instruments to be used to correct for financial exclusion endogeneity are the barrier variables, such as lack of documentation, lack of trust, religious reasons, services being too expensive, being too far away from financial institutions, and lack of money. Lack of money was not included in the regression since this directly affects poverty. The other variables are correlated with the financial exclusion variable but do not directly affect the poverty variable. In line with Imai and Arun (2008); Imai et al. (2010); and Mohammed et al. (2017), the above mechanism can be specified as follows:

$$FE^*_{it} = \theta_0 + X'_{it}\theta + Z'_{it}\gamma + {}_i \qquad (2)$$

$FEi = 1$ if $FEi^* > 0$ and $FEi = 0$ if $FEi^* \leq 0$

Where $(FE_i = 1|X_i, Z_i) = \Phi(\theta_0 + X'_i\theta + Z'_i\gamma)$ and $Pr(FE_i = 0|X_i, Z_i) = 1 - \Phi(\theta_0 + X'_i\theta + Z'_i\gamma)$

FE^*_i is a latent variable; i is the indexed individual; t = 2017, 2014, 2011; X'_i is a vector of the individual characteristics (age, age squared, female, education level, workforce status); Z_i is a vector of dummies variables related to financial exclusion (lack of documentation, lack of trust, religious reasons, services too expensive, far away financial institution); θ and γ are vectors of parameters to estimate; Φ denotes the normal standard cumulative distribution function; and ${}_i$ is a normally distributed error term with a zero mean and a variance equal to 1. The second stage regression helps to determine the effect of financial exclusion on poverty. The treatment effect specification used is specified in Equation 3 as:

$$Pov^*_{it} = \lambda_0 + X'_{it}\lambda + FE_{it}\pi + \eta_i \qquad (3)$$

Where $Povi = 1$ if $Pov^*_i > 0$ and $Povi = 0$ if $Povi^* \leq 0$

The assumption is that ε and η are normally distributed, with a mean of 0 and a variance of 1, and σ_η and maximum likelihood estimation (MLE) were used, respectively. Since there is a selection problem, $Cor(FEi,\eta i) = \rho\ 6 = 0$, the treatment effects version of the Heckman sample selection model with an appropriate instrumental variable (IV) solves this. The variables in Zi are exogenous and are assumed to be correlated with FEi but not with $Povi$. Equation 4 expresses the expected poverty index for those who are financially excluded as: $(\theta^0 + X'\ \ \theta + Z'$

$$[Povit\ |FE_{it} = 1] = X'_{it}\lambda + \pi + \rho\sigma_\eta [\overline{\qquad\qquad}\ {}_{,it}\ \theta + Z'_{,it}{}_{it}\gamma\gamma))] \qquad (4)$$

$\Phi(\theta_0 + X_{it}$

Where φ is the standard normal density function and Φ is the standard normal cumulative distribution function.

The ratio φ to Φ is called the inverse Mill's ratio and helps to determine whether the OLS estimation should be considered or the model estimation should use the MLE.

The expected poverty index for those who are not financially excluded is expressed in Equation 5:

Klover International Journal Economics and Business Administration
Volume 10, Issue 1, January-March 2022
ISSN: 2995-4258
Impact Factor: 7.30
https://kloverjournals.org/journals/index.php/eba

$$\varphi\,(\theta\ +X'\theta\ +Z'$$

$$[Pov_{it}\,|FE_{it}=0]=X'_{it}\lambda\ -\rho\,\sigma_{\eta}\,[\Phi(\theta\ +X'^{it}_{\ \ it}\theta\ +Z'^{it}_{\ \ it}\gamma\,\gamma\,))] \qquad (5)$$

Equation 6 below provides the expected effect of poverty associated with financial exclusion:

$$\varphi\,(.\,)$$

$$[Pov_{it}\,|FE_{it}=1]-[Pov_{it}\,|FE_{it}=0]=\pi\ +\rho\,\sigma_{\eta}\,[\Phi\underline{\qquad\qquad}(.\,)[1-\Phi(.\,)]] \qquad (6)$$

The coefficient δ (estimation from Equation 1) is biased upwards (downwards) if the estimated coefficient of ρ is positive (negative). Since σ_η is positive, the sign and significance of the estimate of $\rho\sigma_\eta$ will show whether any selection bias exists (Imai & Arun, 2008; Imai et al., 2010; Mohammed et al., 2017).

2.2.3. Robustness Check

The Heckman sample selection (Heckman, 1979) only addresses the issue of bias created by the sample in the model. The hypothesis formulated in this study is that financial exclusion increases the poverty level. However, an increase in poverty level could potentially reduce households' access to financial services, leading them to becoming financially excluded. To address this issue, we take advantage of our financial inclusion measure *FEi*, which is binary, and apply the propensity score matching (PSM) estimation proposed by Rosenbaum and Rubin (1983). Since it is not possible to see the counterfactual (here, it is the level of poverty if the individual were financially included), then it will not be possible to observe the level of poverty of financially included individuals. PSM addresses this problem by constructing the counterfactual situation according to the treatment variable. Two groups are formed: the treatment group (financially excluded, *FEi* = 1) and the control group (financially included, *FEi* = 0). By comparing the two groups, we obtained an estimate of the effects of financial exclusion on poverty under the unconfoundedness (treatment assignment is independent of the outcomes, conditional on the covariates) and overlap or common support condition assumptions (the probability of assignment falls between zero and one) (Rosenbaum & Rubin, 1983).

From Caliendo and Kopeinig (2008), in the practical guide for the implementation of propensity score matching, the steps can be summarized in five points:

(1) Determine the observational covariates and estimate the propensity scores from the dataset. The choice of model to determine if the propensity score is problematic, but since our treatment variable is binary, the Logit model is selected.

(2) Choose a matching algorithm. Since each matching algorithm presents advantages and disadvantages, we employed different matching algorithms in our analysis. We used *nearest neighbor*, *radius matching*, *stratification matching,* and *kernel matching*. For further details and formulas regarding these matching algorithms, see, e.g., Becker and Ichino (2002).

(3) Check overlap (region of common support between the treatment and control groups).

(4) Match quality/effect estimation (check whether the procedure can balance the distribution of the relevant variable in both the treatment and control groups). Some of the possible tests are the standardized bias test and the t-test, suggested by Rosenbaum and Rubin (1983), and the stratification test by Dehejia and Wahba (2002).

(5) Conduct sensitivity analysis tests to determine whether the estimated average treatment effect (ATT) on the treated variable is robust.

The estimation procedure for PSM can be summarized following Becker and Ichino (2002) and Imai and Arun (2008). Equation 7 gives the propensity score, which is the conditional probability of been financially excluded given the individual's covariate W, which is a multidimensional vector of individual characteristics defined in *X,* and variables related to financial exclusion summarized in *Z.*

$$p(W) = Pr(FE = 1|W) = E(D|W) \qquad (7)$$

According to Rosenbaum and Rubin (1983), if the exposure to treatment is random within cells defined by W, it is also random within cells defined by the values of the mono-dimensional variable $p(W)$. Equation 8 below estimates the average effect of treatment on the treated (ATT) if the propensity score $p(Wi)$ is known given a population of units denoted by i:

$$\tau \equiv E(Pov_1it - Pov_0it|FEit = 1) = E(E(Pov_1it - P_0i|FEit = 1, p(Wi))) \qquad (8)$$

$$\tau = E(Pov_1it|FEit = 1, p(Wi)) - E(Pov_0it|FEit = 0, p(Wi))|FEit = 1)$$

where i denotes the i^{th} household; t = 2017, 2014, 2011 (the round of the data); and $Povi$ is the potential outcome (poverty likelihood measure) in the two counterfactual situations of being financially excluded or financially included. The two hypotheses needed to derive (7) given (8) are:

(a) Balancing hypothesis (balancing of pre-treatment variables (covariate variables) given the propensity score).

If $p(W)$ is the propensity score, then $FE \perp W \mid p(W)$. This implies that, for a specific propensity score, the financial exclusion program is randomly distributed, thus, on average, households with access to programs and those without are observationally identical. Otherwise, one cannot statistically match households of different categories. *(b) Unconfoundedness given the propensity score.*

If assignment to treatment is unconfounded, i.e., $Pov_1, Pov_0 \perp FE \mid W$, then assignment to treatment is unconfounded given the propensity score, i.e., $Pov_1, Pov_0 \perp FE \mid p(W)$.

3. Results and Discussions

3.1. Descriptive Statistics

Table 3 shows the summary statistics of the 2011, 2014, and 2017 rounds of the survey. Between 2011 and 2017, the education level has improved. This improvement included a free primary schooling policy in 2006 and subsequently, free tuition for girls in the sixth grade in 2010, which has been generalized for girls until the third grade. As shown by the workforce variable in 2017, 27.5% of the Beninese are out of the job market and 62.5% are in the job market. Interviewed individuals in the sample fell within the young age group (with an average age of 33). The main reasons why Beninese people do not have a financial account at a formal financial institution vary from one individual to another. The number of people reporting those reasons has increased over time. Apart from the usual reasons (lack of documentation, financial services being too expensive, and distance to financial institutions), religion is increasingly mentioned as a factor of financial exclusion. It is important to note that in recent years many churches and congregations have been created in Benin.

Table 3. Descriptive statistics of the variables used in the estimation.

Variables	**Definition**	**2011**		**2014**		**2017**	
		Obs.	**% Mean**	**Obs.**	**% Mean**	**Obs.**	**% Mean**
Education	= 1 if secondary school and 0 otherwise	1000	0.329	1000	0.255	1000	0.398
	= 1 if tertiary level and 0 otherwise	1000	0.013	1000	0.005	1000	0.056
Gender	= 1 if female and 0 if male	1000	0.498	1000	0.49	1000	0.456
Age	Individual's age in years	1000	33.57	1000	33.03	990	31.73
Workforce status	= 1 if the individual is out of workforce and 0 otherwise	-	-	-	-	1000	0.275

Far away	= 1 if financial institutions are far away and 0 otherwise	1000	0.193	1000	0.174	1000	0.222
Expensive services	= 1 if financial services are too expensive and 0 otherwise	1000	0.153	1000	0.206	1000	0.221
Lack of documents	= 1 if the individual does not have the necessary documentation and 0 otherwise	1000	0.215	1000	0.305	1000	0.284
Lack of trust	= 1 if the individual does not trust financial institutions and 0 otherwise	1000	0.062	1000	0.204	1000	0.137
Religious reasons	= 1 because of religious reasons and 0 otherwise	1000	0.023	1000	0.012	1000	0.055
Financial exclusion	= 1 if the individual is financially excluded and 0 otherwise	1000	0.460	1000	0.846	1000	0.438
Income quintile	= 1 if included in the 20% poorest and 0 otherwise	1000	0.131	1000	0.158	1000	0.154
	= 1 if included in the 20% second and 0 otherwise	1000	0.165	1000	0.168	1000	0.174
	= 1 if included in the 20% middle and 0 otherwise	1000	0.180	1000	0.171	1000	0.193
	= 1 if included in the 20% fourth and 0 otherwise	1000	0.220	1000	0.208	1000	0.205
	= 1 if included in the 20% richest and 0 otherwise	1000	0.304	1000	0.295	1000	0.274

Table 4. Determinants of financial exclusion.

Variables	**2011**	**2014**	**2017**
Financial institutions are far away	1.314*** (0.456)	0.475*** (0.116)	0.381*** (0.134)
Financial services are too expensive	1.459*** (0.432)	0.185 (0.128)	0.299** (0.127)
Don't have the necessary documentation	1.016*** (0.258)	0.489*** (0.109)	0.400*** (0.110)
Don't trust financial institutions	1.532*** (0.396)	0.086 (0.179)	-0.022 (0.138)
Because of religious reasons	NA NA	-0.899*** (0.324)	0.065 (0.207)
Female	-0.067 (0.120)	0.133 (0.086)	0.243*** (0.088)

Klover International Journal Economics and Business Administration
Volume 10, Issue 1, January-March 2022
ISSN: 2995-4258
Impact Factor: 7.30
https://kloverjournals.org/journals/index.php/eba

Age of individual	-0.155*** (0.025)	-0.069*** (0.013)	-0.045*** (0.014)
Age_squared	0.002*** (0.000)	0.001*** (0.000)	0.000*** (0.000)
Primary school level	1.238* (0.694)	1.034** (0.522)	NA
Secondary school level	0.206 (0.688)	0.706 (0.521)	-0.373*** (0.094)
Completed tertiary or more	NA	NA	-1.082*** (0.237)
Out of workforce	NA	NA	0.546*** (0.100)
Constant	2.973*** (0.819)	-0.003 (0.573)	0.385 (0.267)
Observations	1,000	1,000	990

Note: ***, ** and * signify significance at the 1%, 5% and 10% levels, respectively. Standard errors are in parentheses.

However, is the proliferation of evangelical churches one of the reasons for this financial exclusion? The number of people who reported a lack of trust in financial institutions in 2014 is more than three times the number reported in 2011 and in 2017; the number reported in 2011 has doubled. The political and economic scandal that took place in Benin in 2000 and 2010, referred to as Benin's Madoff scandal, could explain these results. It was based on a Ponzi scheme that consisted of remunerating the first investors with the deposits of new clients, at very high-interest rates, before the system collapsed in 2010. Up to 300,000 people were defrauded, with an estimated total of more than 200 billion FCFA (franc des Colonies Françaises d'Afrique), which roughly coverts to US$500.0000. Following the financial exclusion computation, in 2017, 43.8% of the sampled population in Benin were financially excluded; this figure was 84.6% in 2011. This result confirms that access to financial services in the country is still low (Fund, 2018) and the situation was worsened in 2011. The income distribution in the country through the sampled population shows that income distribution is not shared in the same way and that rich people benefited more than the poor between 2011 and 2017.

3.2. Empirical Results

Table 4 presents the results of the first stage of the treatment effect model to find the determinants of financial exclusion in Benin. The coefficient for the "financial institutions are far away" variable is positive and statistically significant at the 1% level for the 2011, 2014, and 2017 datasets, showing that being far away from financial institutions means that individuals are more likely to be excluded from financial services in Benin. What can justify this result is that when financial institutions are far away, individuals may not be willing to travel to ask for financial services, or they may be reluctant to go since they do not know if they will be eligible or not. The coefficient associated with the "financial services are too expensive" variable is positive and statistically significant at the 1% level for the 2011 and 2017 datasets. This means that financial services are too expensive, which is likely to prevent individuals from visiting financial service institutions in Benin (2011 to 2017). In theory, this is true because when you must pay high interest on a loan or pay a prohibitive price for financial services, you may not be willing to continue using the institution or even use financial services in the first place.

The lack of necessary documentation is more likely to exclude individuals from financial services in Benin since the coefficient associated with this variable is positive and statistically significant at the 1% level since 2011. This is true because financial institutions are reluctant to satisfy individuals' needs when they lack the necessary documentation. In Benin, the situation regarding necessary documentation is critical because most of the population is still without a birth certificate. In addition, it is very difficult to present a valid work certificate while continuing to work in the informal sector, and formal institutions ask for documents that testify or certify your line of work when asking for a loan. Lack of trust in financial institutions is statistically significant at the 1% level for the 2011 dataset, and religious reasons are statistically significant at the 1% level for the 2014 dataset. While the coefficient of correlation between lack of trust and financial exclusion is positive, it is negative between religious reasons and financial exclusion. This reveals that lack of trust in financial institutions is more likely to cause that person to avoid asking for financial services. Religion is one of the factors enabling individuals to have access to financial services (the correlation coefficient between financial exclusion and religion is negative). Throughout these years, the lack of documentation, the distance to a financial institution, and expensive financial services are found to be the main reasons for financial exclusion. Another point to note here is that, in 2011, Beninese citizens did not trust financial institutions, but since 2014, they have started showing an interest in financial institutions by trusting them. The dummy variable for a female is positively correlated and statistically significant at the 1% level with financial exclusion, indicating that females are more likely to be excluded from financial services than males in Benin. This may be because it is more difficult for females to have access to finance because they are less likely to work and have less power in financial decisions. This confirms the findings of the International Monetary Fund (IMF), which shows that males reported higher access to finance than females in Benin (Fund, 2018).

Table 5. Results of the simple probit model.

Variables	**2011**	**2014**	**2017**
Financial_Index	0.566*** (0.089)	0.725 *** (0.145)	0.189 ** (0.090)
Female	0.004 (0.089)	0.113 (0.085)	0.030 (0.087)
Age of individual	-0.003 (0.013)	-0.000 (0.014)	-0.005 (0.013)
Age_squared	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Primary school level	4.476*** (0.133)	4.433 *** (0.133)	NA
Secondary school level	3.909*** (0.156)	4.034 *** (0.155)	-0.566*** (0.094)

Klover International Journal Economics and Business Administration
Volume 10, Issue 1, January-March 2022
ISSN: 2995-4258
Impact Factor: 7.30
https://kloverjournals.org/journals/index.php/eba

Tertiary or higher	NA	NA	-1.082*** (0.247)
Out of workforce	NA	NA	0.030 (0.100)
Constant	-4.970 *** (0.318)	-5.371 *** (0.335)	-0.120 (0.265)
Observations	1,000	1,000	990

Note: *** and ** signify significance at the 1% and 10% levels, respectively. Standard errors are in parentheses.

Education also plays a key role in financial markets. As expected, the findings in Benin are not surprising. The coefficients associated with the education variable (secondary, tertiary or higher levels of education) are negative and significant at the 1% level correlated with financial exclusion, meaning that the more educated you are, the less likely you are to be financially excluded. Furthermore, the regression results for the 2011, 2014, and 2017 datasets show that younger individuals are less likely to be excluded from financial services and are more likely to be excluded as they get older (the age and age squared coefficients are respectively negative and positive and statistically significant at the 1% level). Finally, individuals who are not in the job market are more likely to be unable to access financial services than their peers. This result can be explained by the fact that the job market is largely informal so individuals do not have valid documents to present to financial institutions to get a loan or credit.

Tables 5 and 6 present the results of the regression of financial exclusion on poverty where the first and second 20% poorest income quintiles are used as proxies. As we can expect, the coefficient of the financial exclusion is positive and statistically significant at the 1% level for all three rounds of the surveys (2011, 2014, and 2017). This means that financially excluded individuals are more likely to be poor. In other words, having access to financial services help to reduce poverty in Benin. These results are consistent with the ongoing literature in Benin.

Table 6. Treatment effect model.

Variables	**2011**	**2014**	**2017**
Financial_Index	0.557 *** (0.093)	0.800 *** (0.159)	0.204** (0.094)
Female	-0.004 (0.091)	0.110 (0.085)	0.046 (0.093)
Age of individual	-0.000 (0.015)	-0.007 (0.015)	-0.007 (0.014)
Age_squared	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)
Primary school level	4.405 *** (0.245)	4.561 *** (0.206)	NA

Secondary school level	3.858 *** (0.212)	4.092 *** (0.195)	-0.596*** (0.110)
Tertiary or higher	NA	NA	-1.181*** (0.301)
Out of workforce	NA	NA	0.066 (0.121)
Invmills1	-0.074 (0.213)	0.245 (0.209)	0.106 (0.197)
Constant	-4.893 *** (0.391)	-5.465 *** (0.376)	-0.167 (0.280)
Observations	1,000	1,000	990

Note: *** and ** signify significance at the 1% and 10% levels, respectively. Standard errors are in parentheses.

Dahoun et al. (2013) assessed the impact of microcredit on the empowerment of poor females in Benin. The study found that microcredit has a positive effect on the empowerment of (mainly poor) female household heads. Sylli (2012) showed that microcredit contributes to the living conditions of the beneficiary and helps to reduce poverty with more medium- and long-term credit for agricultural activities. Djossou et al. (2016) found a positive and significant effect of access to microcredit services on poverty in Benin. The difference between Tables 5 and 6 is that the results of Table 5 are biased, but the treatment effect version of Heckman's sample selection model will correct that. In Table 6, the Inverse Mills Ratio coefficient is not statistically significant for anyone in the 2011, 2014, and 2017 datasets. Following Imai et al. (2010), this insignificant result can be interpreted as the absence of selectivity bias from the regression of the simple probit model. From these results, education level has a positive and significant impact on poverty. Gender, age, and workforce status appear to have no significant effect on poverty in Benin. The limited number of observations in this study may be the main reason for these insignificant results.

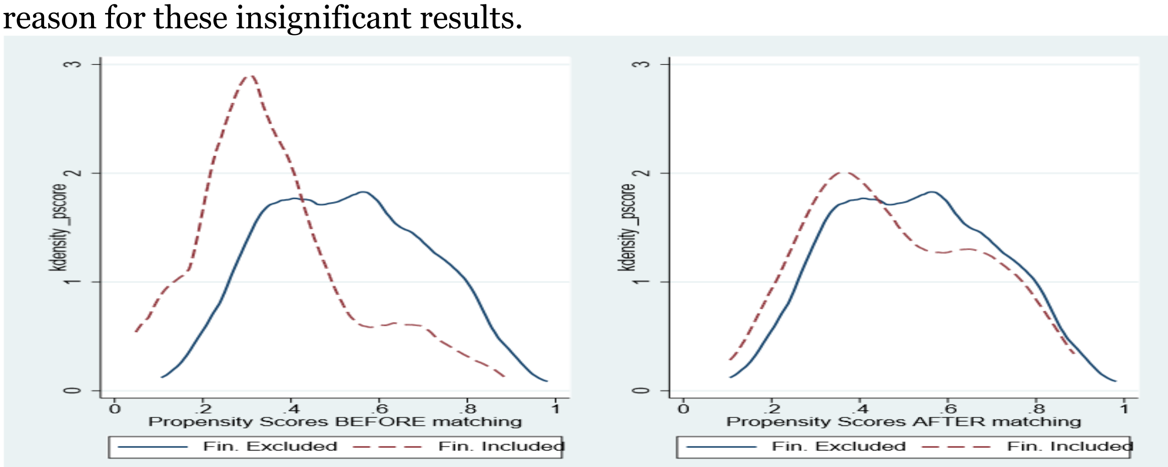

Figure 1. Density of the propensity scores before and after matching (2017).

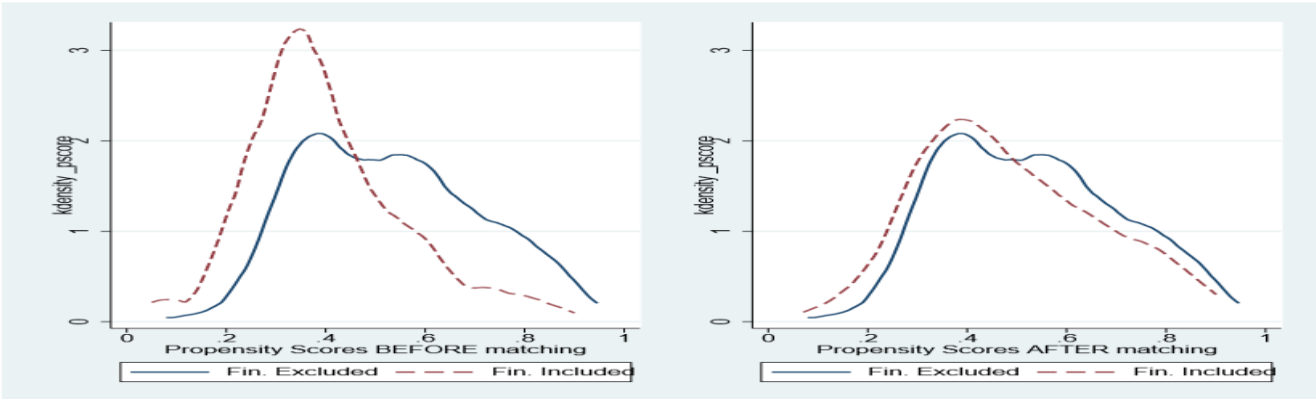

Figure 2. Density of the propensity scores before and after matching (2014).

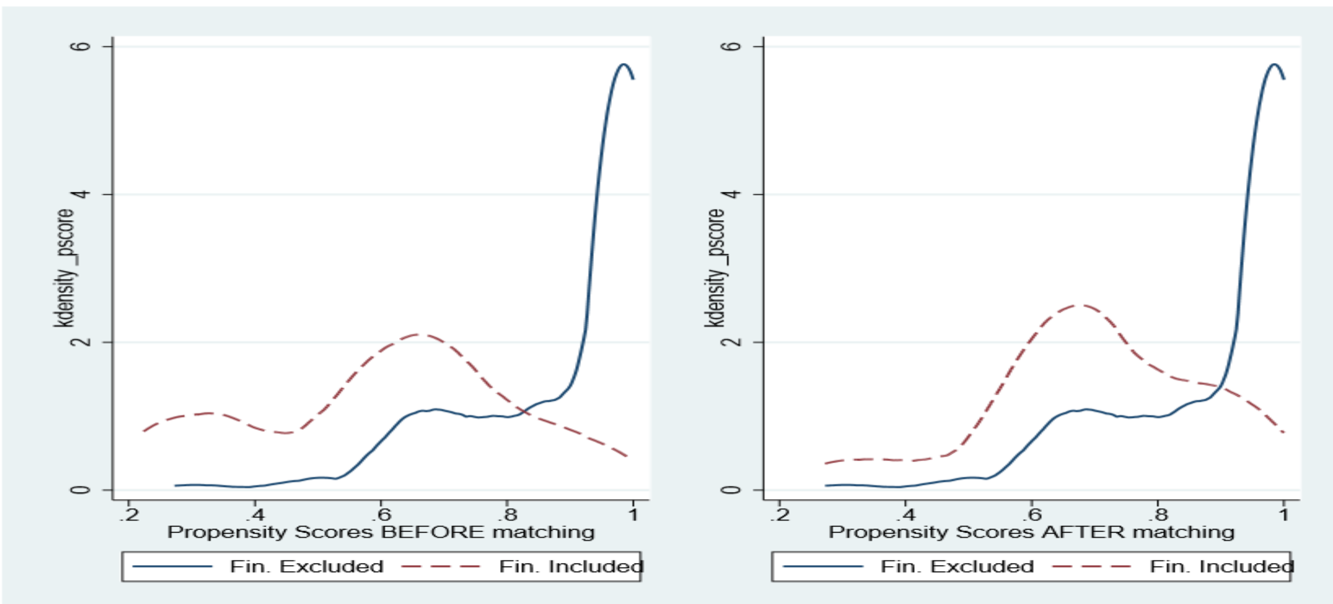

Figure 3. Density of the propensity scores before and after matching (2011).

3.3. Robustness Checks

The Figures 1, 2, and 3 present the density of the propensity scores before and after matching. From these figures, the treated group (financially excluded individuals) are in the blue, and the untreated group (financial included) are in red. The distribution of the probability (propensity score) for 2014 and 2017 can be considered as normal distribution patterns. These figures also show that it is easier to find matches (not clear that they will be the best matches) between treated and untreated units since there is a full distribution of probability along with the common support. For 2011, the trend before and after matching is the same, but treated and untreated individuals follow different patterns. Table 7 presents the results of this model using different matching algorithms: nearest neighbor, radius, kernel, and stratification. The results show that the ATT for each matching algorithm by year is approximately the same and is statistically significant at the 1% level for most of them (financially excluded individuals are more likely to be poorer than their peers who are financially included).

Table 7. PSM model results with different matching algorithms.

Volume 10, Issue 1, January-March 2022
ISSN: 2995-4258
Impact Factor: 7.30
https://kloverjournals.org/journals/index.php/eba

Matching algorithms	2011	2014	2017
Nearest Neighbor	0.167*** (0.036) [2.225]	0.080** (0.015) [11.001]	0.054 (0.035) [1.552]
Radius	0.136*** (0.022) [6.310]	0.145*** (0.017) [8.503]	0.056*** (0.025) [2.292]
Kernel	0.128*** (0.025) [5.075]	0.164*** (0.015) [10.683]	0.048* (0.27) [1.786]
Stratification	0.132*** 0.023 5.729	0.165*** 0.014 11.989	0.050 0.027 1.847
Observations	1,000	1,000	1,000

Note: Bootstrapped standard errors are in parentheses and P-values are in square brackets. *, ** and *** signify significance at the 1%, 5% and 10% levels, respectively.

For the nearest neighbor matching algorithm, financially excluded individuals are 8% and 16.7% more likely to be poor than financially included individuals in 2014 and 2011, respectively. The radius matching algorithm shows that financially excluded individuals are 13.6%, 14.5%, and 5.6% more likely to be poorer than financially included individuals, respectively, in 2011, 2014, and 2017. These results are statistically significant at the 1% level. For the kernel and stratification matching algorithms, financially excluded individuals are respectively 4.8% and 5% more likely to be poorer than their peers in 2017; 12.8% and 13.2% are more likely to be poorer than financially included individuals in 2014; and 16.4% and 16.5% are more likely to be poorer than non-financially excluded individuals in 2011.

4. Conclusion

This study contributes to the growing literature on the impact of financial inclusion on poverty reduction by exploring determinants of multidimensional financial inclusion (account ownership, credit access, savings, financial resilience, financial account use, and online transactions) and by examining the potential impact of financial inclusion on poverty with specific reference to Benin using three rounds of data (2011, 2014 and 2017) from the World Bank's microdata from the Benin Global Financial Inclusion Index survey. First, the study employed the probit model to assess determinants of financial exclusion and found, on the one hand, a positive and significant relationship between lack of documentation, expensive financial services, being far away from financial institutions, religion, lack of trust in financial institutions, and financial exclusion, and on the other hand, a significant relationship was found between individual characteristics (such as gender, age, education, and workforce level/status) and financial exclusion. Second, the treatment effects version of Heckman's sample selection model (Heckman, 1979) was used to address the issue of endogeneity and selection problems related to financial exclusion and shows that financial exclusion in Benin has a positive and significant effect on poverty. In the robustness check, the study employed the propensity score matching (PSM) estimation technique, and the outputs of this model confirm the results. The estimation of the potential impact of financial exclusion on poverty measured by the first and second 20% poorest individuals in Benin shows that financially excluded individuals are more likely to be poorer than financially included individuals. An implication of this is that policymakers and governments should implement policies that will promote financial services development while focusing on reducing the poverty rate. To further reduce income inequality, more measures must be taken to address the financial exclusion of low-income groups in Benin from financial services. In this context, programs that will help alleviate poverty will likewise address the growing income inequality in the country. Similarly, to promote inclusion and access to financial services, policymakers and government should focus more on how to decentralize financial institutions/financial programs and bring them closer to the population since the distance from financial institutions plays a determinant role in financial exclusion. In addition, the government should make access to financial services less costly and help people without the necessary documentation by implementing programs that can include those without basic documents such as a birth certificate and a national identity card.

References

Afolabi, J. (2020). Impact of financial inclusion on inclusive growth: An empirical study of Nigeria. *Asian Journal of Economics and Empirical Research, 7*(1), 8-14.Available at: https://doi.org/10.20448/journal.501.2020.71.8.14.

Alkire, S., & Santos, M. E. (2014). Measuring acute poverty in the developing world: Robustness and scope of the multidimensional poverty index. *World Development, 59*, 251-274.Available at: https://doi.org/10.1016/j.worlddev.2014.01.026.

Allen, F., Demirguc-Kunt, A., Klapper, L., & Peria, M. S. M. (2016). The foundations of financial inclusion: Understanding ownership and use of formal accounts. *Journal of Financial Intermediation, 27*, 1-30.Available at: https://doi.org/10.1016/j.jfi.2015.12.003.

Anthony, Y. N., Hadrat, Y., George, T., Kwasi, A., & Samuel, T. B. (2021). The effect of financial inclusion on poverty reduction in Sub-Sahara Africa: Does threshold matter? *Cogent Social Sciences, 7*(1), 1903138.Available at: https://doi.org/10.1080/23311886.2021.1903138.

Aportela, F. (1999). Effects of financial access on savings by low-income people. Bank of Mexico, Research Department. Retrieved from: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.194.5270&rep=rep1&type=pdf.

Becker, S. O., & Ichino, A. (2002). Estimation of average treatment effects based on propensity scores. *The Stata Journal, 2*(4), 358-377.Available at: https://doi.org/10.1177/1536867x0200200403.

Bruhn, M., & Love, I. (2014). The real impact of improved access to finance: Evidence from Mexico. *The Journal of Finance, 69*(3), 13471376.Available at: https://doi.org/10.1111/jofi.12091.

Caliendo, M., & Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys, 22*(1), 31-72.Available at: https://doi.org/10.1111/j.1467-6419.2007.00527.x.

Dahoun, D. B., Manlan, O., Vodonou, C., Mongan, S. M., Mededji, D., & Alofa, J. P. (2013). Microcredit, poverty and the empowerment of women in Benin (No. 160426). Partnership for Economic Policy (PEP).

Dehejia, R. H., & Wahba, S. (2002). Propensity score-matching methods for nonexperimental causal studies. *Review of Economics and Statistics, 84*(1), 151–161.Available at: https://doi.org/10.1162/003465302317331982.

Demirgüç-Kunt, A., & Singer, D. (2017). Financial inclusion and inclusive growth: A review of recent empirical evidence. World Bank Policy Research Working Paper, No. (8040).

Djossou, G. N. A., Monwanou, D. I., & Novignon, J. (2016). *Improving access to microcredit in Benin: Are the poor and women benefiting?* Germany: University Library of Munich.

Dollar, D., & Kraay, A. (2002). Growth is good for the poor. *Journal of Economic Growth, 7*(3), 195-225.

Du Volet, R. D., & Du Temps, E. (2015). Integrated modular survey on household living conditions 2nd edition (emicov-2015). Retrieved from https://www.scirp.org/(S(czeh2tfqw2orz553k1w0r45))/reference/referencespapers.aspx?referenceid=3040514.

Dupas, P., & Robinson, J. (2010). Savings constraints and microenterprise development: Evidence from a field experiment in Kenya. *American Economic Journal: Applied Economics, 5*(1), 163-192.Available at: http://dx.doi.org/10.1257/app.5.1.163.

Efobi, U., Beecroft, I., & Osabuohien, E. (2014). Access to and use of bank services in Nigeria: Microeconometric evidence. *Review of Development Finance, 4*(2), 104–114.Available at: https://doi.org/10.1016/j.rdf.2014.05.002.

Fund, I. M. (2018). Selected issues paper for Benin. Country Report No. 18/2.

Gupte, R., Venkataramani, B., & Gupta, D. (2012). Computation of financial inclusion index for India. *Procedia-Social and Behavioral Sciences, 37*, 133-149.Available at: https://doi.org/10.1016/j.sbspro.2012.03.281.

Heckman, J. J. (1979). Sample selection as a specification error. *Econometrica, 47*, 153–161.Available at: https://doi.org/10.2307/1912352.

Imai, K., & Arun, T. (2008). Does microfinance reduce poverty in India? Economics, The University of Manchester, The School of Economics Discussion Paper Series No. 0814.

Imai, K. S., Arun, T., & Annim, S. K. (2010). Microfinance and household poverty reduction: New evidence from India. *World Development, 38*(12), 1760-1773.Available at: https://doi.org/10.1016/j.worlddev.2010.04.006.

Mohammed, J. I., Mensah, L., & Gyeke-Dako, A. (2017). Financial inclusion and poverty reduction in Sub-Saharan Africa. *African Finance Journal, 19*(1), 1–22.

Park, C. Y., & Mercado, R. (2015). Financial inclusion, poverty, and income inequality in developing Asia. Asian Development Bank Economics Working Paper Series, No. (426).

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika, 70*(1), 41-55.Available at: https://doi.org/10.1093/biomet/70.1.41.

Sarma, M. (2008). Index of financial inclusion, indian council for research on international economic relations (icrier) (Tech. Rep.). Working Paper No. 215.

Sylli, J. H. (2012). *Microcredit in the program to combat poverty among women in Benin: myth or reality?* , Collection: Theses and Dissertations, Grantor.

Timothy, P. O. (2019). Financial inclusion and health shocks: A panel data analysis of 36 African countries. *Asian Journal of Economics and Empirical Research, 6*(1), 45-51.Available at: https://doi.org/10.20448/journal.501.2019.61.45.51.

Tita, A. F., & Aziakpono, M. J. (2017). The effect of financial inclusion on welfare in Sub-Saharan Africa: Evidence from disaggregated data. Economic Research Southern Africa, Working Paper No. 679.

Zhang, Q., & Posso, A. (2017). Thinking inside the box: A closer look at financial inclusion and household income. *Journal of Development Studies, 55*(7), 1616-1631.Available at: https://doi.org/10.1080/00220388.2017.1380798.