

Original Paper

The Impact of Savings and Credit Cooperatives on Household Welfare: Evidence from Uganda

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Abstract

Savings and Credit Cooperatives (SACCOs) help in reducing the financial exclusion gap. This study examines whether SACCOs improve the welfare of households. Data used are from 2009/2010 and 2010/2011 World Bank's Living Standards Measurement Surveys (LSMS) done in Uganda by the Bureau of Statistics. Treatment cases are households that saved in SACCOs only while control cases are those that did not use the services nor save in SACCOs, banks or microfinance institutions. Propensity Score Matching and a two-step Treatment Effects' model are used. Findings show that SACCOs have a positive and significant impact on household dietary diversity score, food consumption score, household clothing/footwear expenditure, and school enrollment rates in Uganda. The results are robust to hidden selection bias. The results show that SACCOs play a key role in improving household food security, non-food expenditure, and human capital development for the poor facing financial exclusion from banks and traditional microfinance institutions.

Keywords

SACCOs, Household Welfare, Impact Evaluation, Uganda

JEL Classifications: C21, C26, D14, G21

1. Introduction

Global poverty reduction, especially in developing countries, is one of the key points of focus by the Sustainable Development Goals (SDGs). Development experts recognize that poverty reduction and improved access to financial markets by households are two very closely related facts. However, financial exclusion from the traditional financial services is widespread in most developing countries. In Africa, less than one in five households has access to credit (Beck et al., 2009). Over the last three

decades microfinance has emerged to address this gap with savings and credit services tailored to the needs of the poor (small loans and deposits; modified collateral, etc.). Empirical research shows that improved access to microfinance by the poor in developing countries facilitates their ability to increase and diversify household incomes, generate human and social capital as well as accumulate wealth. In addition, microfinance has enabled the poor invest in improved access to schooling, better food-security and nutrition, improved health, better housing, business expansion, women's empowerment and employment (Van Rooyen, Stewart, & De Wet, 2012; Hietalahti & Linden, 2006; Beck, Demirguc-Kunt, & Levine, 2004; Christen, Lyman, & Rosenberg, 2003; Afrane, 2002; Robinson, 2001; Yunus, 1999; Barnes & Keogh, 1999; Barnes, 1996). There are those who argue that microfinance does not alleviate poverty. Their view is that microfinance does not benefit the poorest people but only benefits the middle or upper poor (Banerjee, Duflo, Glennerster, & Kinnan, 2015; Adjei & Arun, 2009; Kondo, Orbeta Jr, Dingcong, & Infantado, 2008; Coleman, 2006; Amin, Rai, & Topa, 2003; Hulme & Mosley, 1997). Others found no empirical evidence of increased household income or consumption in the short run, but found other potential benefits (Duvendack et al., 2011). In our study we make the argument that improved access to microfinance through Savings and Credit Cooperatives (SACCOs) actually improves the welfare of poor households in Uganda. The motivation for our study is that there is no rigorous empirical econometric evidence on the impact of SACCOs on household welfare in Africa. SACCOs are semi-formal institutions and are quite different from the traditional well established microfinance institutions which normally target the middle poor. The contribution of this study is the generation of rigorous econometric evidence of the impact of SACCOs on the welfare of poor households in developing country setting. Most of the evidence generated in the literature is for traditional microfinance organizations but not SACCOs.

2. Overview of the Literature

There have been studies that show the positive impact of microfinance in developing countries. Hartarska & Nadolnyak (2008) indicate that microfinance is an effective way of providing cheap financial services to poor individuals and families. It plays a crucial role in the growth of developing economies by improving the welfare of the poor (Cheng & Degryse, 2010; Khandker, 2005; Bhatt & Tang, 2001). It reduces poverty by increasing incomes, health care, nutrition and education attainment, and women empowerment (Hermes & Lensink, 2011; Khandker, 2005; Dunford, 2001; Morduch, 2000, 1998). It is argued that gender equality and leadership opportunities are enhanced (Goetz & Gupta, 1996). Proponents of microfinance argue that limited access to credit often leads to precautionary savings which are not in the form that is useful to boost agricultural production (Lorenzoni & Guerrieri, 2011; Udry, 1994). In fact Collins et al. (2010) argue that lack of access to credit is among the major causes of the poverty traps faced by poor households in developing countries.

Microfinance has lifted the poor out of poverty by raising household incomes and consumption (Dupas & Robinson, 2013; Wright, 2011; Khandker, 2001; Chen & Snodgrass, 2001; Dunn & Arbuckle, 2001;

Zaman, 1999; Pitt & Khandker, 1996; Hossain, 1988). Microfinance has improved educational attainment and improved health status (Pitt et al., 1999; Pitt & Khandker, 1996). Therefore there is a host of literature that shows the positive impact of microfinance (Agbola et al., 2017; Banerjee et al., 2015; Karlan & Zinman, 2011; Stewart et al., 2010).

Opponents of microfinance have often suggested negative effects of microfinance on poor by arguing that it creates vicious cycles of debt, dependency, increased workloads and domestic violence (Copestake, Bhalotra, & Johnson, 2001; Morduch, 1998). Competition among microcredit suppliers leads to multi-loans, rising default rates, over-indebtedness with negative outreach (Srinivasan, 2010). Those opposed to microfinance have argued that it does not alleviate poverty but benefits only the middle and upper poor and not the poorest of the poor (Banerjee et al., 2015; Kondo et al., 2008; Hulme & Mosley, 1997). Others argue there is no empirical evidence of increased household income or consumption in the short run but show other potential benefits (Duvendack et al., 2011). The literature on randomized evaluations or field experiments on the impacts of savings on school enrollment find no statistically significant impacts (Prina, 2015; Baro et al., 2013). Prina (2015) finds that for households who have access to bank savings accounts in Nepal, there is no statistically significant impact on school enrollment, but finds that the intervention raises investment in education, in the form of textbooks and school uniforms. Baro et al. (2013) evaluate the Saving for Change (SfC) program in Mali and find no statistically significant impact of saving on school enrolment or expenditure.

3. An Overview of SACCOs in Uganda

This study focuses on the impact of Savings and Credit Cooperative Organizations (SACCOs) on the welfare of the member households in Uganda. SACCOs are akin to Rotating Savings and Credit Associations (ROSCAs) but are more formal institutions. An estimated 2.2 million Ugandans are ROSCA members. In a ROSCA all the members contribute a fixed amount of money each week, the total of which is given to one of the members. This cycle is repeated until every member receives the fund at least once, that is, the funds rotate around the members (Peterlechner, 2009). However, SACCOs are more advanced financial institutions that are owned, managed and run by their members who have a common bond, such as geographic location, same business organization or employer, same community and members possess equal voting rights (Brian Branch, 2005). Objectives of a typical SACCO include promoting the welfare and economic interests of its members, providing savings facilities and credit at favorable interest rates, training of members in business skills, poverty reduction and cooperation. Armendáriz de Aghion and Morduch (2005) show that SACCOs are financial institutions that plays a very important role of providing microfinance services around the world. In Uganda, the government has encouraged the formation of SACCOs to increase outreach and access to financial services by the poor in rural areas. SACCOs offer commercial and agricultural loans at interest rates of 13% and 9%, respectively. It is estimated that by the end of 2010, SACCOs in the country had outstanding loans of Shs 292 billion (US\$132.73 million), net savings of Shs 208 billion

(US\$94.55 million), share capital of Shs 178 billion (US\$80.91 million) and income of about Shs 60 billion (US\$27.27 million). Through the Ministry of Trade, Industry and Cooperatives (MTIC), the government invested US\$ 134 million for subsidized loans to individuals and small businesses through the government-owned Microfinance Support Center (MSC) to SACCOs (MTIC, 2016). A survey done in Uganda by EPRC (2013) reveals that SACCOs which were legally constituted, but not controlled by the central bank were an option of choice second to commercial banks in terms of adults holding an account at a financial institution. The share of the adult population that operated an account increased from 5% percent in 2009 to 21% in 2013. The study also reveals that about 61% of the total users of SACCOs were women and 87% of all adult users of SACCOs were in the rural areas of Uganda (EPRC, 2013). As indicated above, SACCOs are a potential source of financial services to a large fraction of Ugandans who are excluded from commercial banks and traditional microfinance institutions. By 2013 there were 1,900 operational SACCOs in Uganda. However, many SACCOs have organizational challenges that impede their service delivery. These include lack of proper financial oversight and capacity, poor bookkeeping, and inadequately skilled staff and boards (BoU & MoFPED, 2017). Some literature indicates that governance remains the major weakness SACCOs in developing countries (Lapie & P  rilleux, 2008; Cuevas & Fischer, 2006; Cornforth, 2004; Branch & Baker, 2000). Our contribution to the literature is that we examine the impact of SACCOs on household welfare in Uganda and to the best of our knowledge there has not been any rigorous study that has examined this impact in terms predefined household outcomes. We provide a rigorous econometric impact assessment of SACCOs using propensity score matching methods that are complemented by the two-step treatment effects model with bootstrap corrected standard errors.

4. Methodology

4.1 Propensity Score Matching (PSM) Methodology

4.1.1 Background

To evaluate the impact of access to SACCO services on household welfare, we first control for potential differences between the treatment and control cases. In this study we restrict our sample to households that use the services and actually save in SACCOs only (treatment cases) and compare them with those that do not use the services nor save in any formal or semiformal financial institution, such as banks, microfinance institutions, SACCOs, etc. (control cases). To control for possible hidden selection bias, this study adapts the propensity score matching (PSM) method following Rosenbaum and Rubin (1983), Dehejia and Wahba (2002), Jalan and Ravallion (2003), DiPrete and Gangl (2004), Smith and Todd (2005), Mendola (2007), and Caliendo and Kopeinig (2008). The advantage of using PSM is that it does not require exclusion restrictions or a given specification of the functional form of the selection model to construct the counterfactual as well as reduce self-selection bias. Denote the indicator variable for participation in a program or treatment as $D = 1$ for participants and $D = 0$ for non-participants. For a given treatment we have the observed mean outcome under the condition of

treatment, $E[Y_1 | D = 1]$, and the unobserved mean outcome that the subject would have realized had they not indeed experienced the treatment, $E[Y_0 | D = 1]$. Similarly, for a given control subject we have the observed mean outcome under the condition of non-treatment, $E[Y_0 | D = 0]$, and the unobserved mean outcome that the control subject would have realized had they experienced the treatment, $E[Y_1 | D = 0]$. Following Rosenbaum & Rubin (1983) and Caliendo & Kopeinig (2008), the parameter of interest in this study is the average treatment effect on the treated group (ATT) where

$$(1) \text{ATT} = E[Y_1 - Y_0 | D = 1] = E[Y_1 | D = 1] - E[Y_0 | D = 1].$$

In practice we observe the mean outcome $E[Y_0 | D = 0]$ but do not observe mean outcome, $E[Y_0 | D = 1]$. We thus use PSM to extract for comparison the observed mean outcome of the non-treatment cases, $E[Y_0 | D = 0]$ that are most similar in observed characteristics to the treatment cases, $E[Y_1 | D = 1]$. That is, we use $E[Y_0 | D = 0]$ as a proxy for the unobserved counterfactual, $E[Y_0 | D = 1]$. For the ATT to be free from self-selection bias we have,

$$(2) E[Y_0 | D = 1] = E[Y_0 | D = 0]$$

To fulfill the condition in (2) there is the conditional independence and the common support assumptions (Rosenbaum & Rubin, 1983). The predicted probability for each household is the propensity score, $P(x) = \Pr(D = 1 | X)$ and the overlap condition implies that $0 < \Pr(D = 1 | X) < 1$. From (2) we have

$$(3) \text{ATT} = E[E[Y_1 | D = 1, P(x)] - E[Y_0 | D = 0, P(x)]]$$

4.1.2 Testing the Quality of PSM Matching

We test the quality of matching to make sure that none of the observable characteristics are significantly different between treatment and control households after matching to reduce the effects of confounding observable characteristics. In addition, both the likelihood ratio chi-square statistic for the joint significance of all covariates and the pseudo- R^2 from the probit/logit of treatment status on covariates should decline after matching. The joint significance of all covariates should be rejected as given by the high p-value of the likelihood ratio chi-square statistic (Rosenbaum & Rubin, 1983).

4.1.3 Testing Robustness of Results

Before matching the treatment and control samples, the two cohorts differ in both observed and unobserved characteristics. After matching and controlling for the quality of matching, the assumption is that there might be an unobserved confounding factor that explains why there are differences between the treatment and control households, for instance, in terms of the level food security or normalized household expenditure. Following Rosenbaum (2002, 1987) we generate estimates of the magnitude of hidden selection bias that are necessary to invalidate the ATT study findings. That is, Rosenbaum bounds sensitivity analysis determines how strongly an unobserved confounding characteristic biases the selection process. Rosenbaum (2002, 1987) developed the parameter gamma (Γ) to represent the odds of receiving treatment. In a randomized controlled trial, all respondents have the same odds of receiving treatment, so $\Gamma = 1$. In an observational study, at 5% or 10% level of significance, the closer Γ is to the value of 1.0, the more sensitive the more sensitive the findings are to

small amounts of hidden selection bias. For instance, with a value of $\Gamma=1.10$ at 5% or 10% level of significance, there should be concern that hidden selection bias is a serious threat to the validity of the study findings. In this study we consider the value of $\Gamma = 1.20$ at 10% level of significance as the lowest cut-off safe point that is far enough away from $\Gamma=1.0$ to allay concerns about the influence of unobserved confounding on the ATT study findings. We supplement the Rosenbaum Γ tests with another test for hidden selection bias. Following Jalan & Ravallion (2003, 1999), we also test for potential remaining hidden selection bias of confounding factors using the Sargan-Wu-Hausman test. We do this only on the sample of matched treatment and control households using Nearest Neighbor matching. Using only the matched sample of treatment and control households, we run an OLS regression of the outcome variable on the residuals from the probit selection equation, the propensity score, and a set of additional control variables that exclude the instruments used to identify exogenous variation in the outcome variable. If the coefficient on the residuals is significantly different from zero, then hidden selection bias is still a problem even after matching and it may compromise the estimate of the impact. If the coefficient on the residuals is not statistically significant, then we can assert that the impact estimate is a result of participation in the treatment.

4.2 The Treatment Effects Model (Switching Regression Model)

The decision to join and hold savings in a SACCO might not be exogenous to the households so we test whether or not assignment to treatment is endogenous using the Wu-Hausman test. We test the null hypothesis that assignment to treatment is exogenous. If the null is rejected, then we employ the two-step treatment effects model that also explicitly controls for hidden selection bias and compare the results to those obtained using PSM. We denote the outcome variable as Y_i , and the treatment selection variable as $D = 1$ for the treatment households and $D = 0$ for the control households and \mathbf{x}_i as a vector of explanatory variables. We have the OLS outcome regression model given by:

$$(4) Y_i = \beta' \mathbf{x}_i + \delta D_i + \varepsilon_i$$

where δ is the estimate of the impact of SACCOs on the outcome variable and ε_i is the error term. However, confounding factors will bias the estimate of δ . Therefore we use two-stage least squares approach while controlling for hidden selection bias. The first stage is the probit model that regresses the treatment selection variable, D_i , on the vector \mathbf{x}_i of explanatory variables and a vector \mathbf{z}_i , of instruments. Denoting the D_i^* as the latent treatment selection variable, we have:

$$(5) D_i^* = \theta' \mathbf{w} + u_i,$$

$$D_i = 1 \text{ if } D_i^* > 0,$$

$$D_i = 0 \text{ if } D_i^* \leq 0,$$

The regression model observed only if $D_i=1$ is given as:

$$(6) Y_i = \beta' \mathbf{x}_i + \varepsilon_i$$

Thus

$$(7) E [Y_i | D_i = 1] = \beta' \mathbf{x}_i + \beta_\lambda \lambda(\theta' \mathbf{w})$$

where the sample selectivity correction, $\lambda(\theta' \mathbf{w})$ is the inverse Mills ratio or the hazard function for the

incidentally truncated distribution. Therefore the selection probit model is

$$(8) D_i = \beta'x_i + \gamma'z_i + v_i$$

The predicted values of the treatment selection variable in (8) are used in the second stage OLS regression given by:

$$(9) Y_i = \beta'x_i + \delta_{IV}D + \beta_\lambda(\theta'w) + \varepsilon_i$$

where the treatment impact is now given by the parameter δ_{IV} and the instrument variables in the vector z_i , are assumed to be correlated with treatment D , but not with the error vector ε_i .

5. Data

5.1 Data Sources

The study uses household survey data from the World Bank's Living Standards Measurement Surveys (LSMS) for Uganda. The LSMS for Uganda is the Uganda National Panel Survey (UNPS), which consists of a sample of about 3,200 households, all previously interviewed as part of the 2005/2006 Uganda National Household Survey (UNHS). The UNPS is conducted in two visits, where a household is interviewed twice in a year with the visits six months apart. This is done in order to capture agricultural information, because Uganda has two cropping seasons. Data collected during the UNPS are at individual, household, and community levels and these include, *inter alia*, data on education, health, income, expenditure, wealth, infrastructure and services. The UNPS involves tracking and re-interviewing about 3,200 households that are distributed over 322 enumeration areas (EAs) which are selected out of 783 EAs that were initially visited under the 2005/06 UNPS. The UNPS data used in our study covers the initial sample that was visited in the period 2009/2010 and 2010/2011. The 2009/2010 UNPS sample used in our study consists of 2,975 households. This figure is lower than that sampled in 2005/2006 period due to attrition. The 2010/2011 UNPS sample consists of 2,716 households due to attrition. We restrict our analysis to the 2009/2010 and 2010/2011 UNPS household samples due to availability of detailed information on household financial services.

5.2 Indicator and Outcome Variables

In this study we restrict our sample to households that use the services of and actually saved in SACCOs only (treatment group) and compare them with those that do not use the services of nor save in banks, microfinance institutions and SACCOs or any formal or semi-formal financial institution (control group). The indicator variable is SACCO that takes a value of 1 for treatment cases and a value of zero for control cases. We define SACCO saving households as those hold savings in a SACCO only and not in banks or microfinance institutions. In most cases these households will have borrowed in the past from the SACCOs. We exclude households that only applied to borrow but did not save in the SACCOs. We investigate the impact of access to SACCOs services, in this case holding savings in a SACCO on household welfare with respect to four outcome variables, which include (i) the household dietary diversity score (HDDS); (ii) the food consumption score (FCS); (iii) household clothing and footwear expenditure; and (iv) school enrollment ratio. The HDDS and FCS are both standard proxy

indicators for food security, which capture household food consumption and dietary diversity (Kennedy et al., 2011; Kennedy et al., 2010; Hoddinott & Yohannes, 2002).

The HDDS uses a standard list of 16 food groups aggregated into 12 main groups with all the food categories having the same weight (WFP & FAO, 2012; Kennedy et al., 2011). It uses a 24 hour recall period and is an indication of household access to food and nutrition. However, due to data limitations, we computed the HDDs as the average number of Yes scores (Yes = 1; No = 0) for the number of different food categories consumed by the each household in the last seven days prior to the UNPS. For instance, a score of 8 indicates the household consumed eight different food groups in the last seven days prior to the interview. The different categories considered in our study were: (a) cereals (includes rice, maize, sorghum, millet, bread, porridge, beer residue); (b) pulses/legumes (includes beans, groundnuts, peas, sesame, green grams, sunflower); (c) roots/tubers (includes cassava, sweet potatoes, potatoes, yams); (d) vegetables (includes greens, cabbages, okra, kale, spinach, tomatoes, onions); (e) all types of fruit and fruit juices; (f) meats, poultry, offals, blood; (g) any fish type; (h) eggs; (i) milk/milk products (excluding ghee, butter); (j) oils/fats(including ghee, butter); (k) sugar/honey (including sugarcane and molasses); (l) coffee, tea, condiments. The number of Yes = 1 scores for each household reflect the nutritional quality of the diet. A higher HDDS indicates a higher level of access to food and nutritional quality.

Following the FAO, we computed the Food Consumption Score as a composite score based on 8 major food categories that any household member has consumed over the previous 7 days, multiplied by the number of days that the food category was consumed after being weighted by the nutritional importance of the food category. The total possible score ranges from 0 to 112. The major food categories were (a) main staples (cereals/tubers) with a weight of two; (b) pulses/legumes with a weight of three; (c) vegetables with a weight of one; (d) fruits/fruit juices with a weighted of one; meats, poultry, offals, blood, any fish type with a weight of 4; milk and milk products with a weight of 4; sugar/honey with a weight of 0.5, and oil and fats with a weight of 0.5 (WFP & FAO, 2012; Kennedy et al., 2011; WFP, 2009, 2008).

Annual household expenditure on clothing and footwear was computed for each household for the 2009/2010 and 2010/2011 samples. School enrollment ratio was computed as the sum of number of children in primary, secondary and tertiary institutions divided by the total number of children in the household. Following Khandker (2005) we generate the vector z_i of instruments used in the treatment effects selection equation as follows. We choose the number of residential houses and number of commercial buildings owned by the households as two instruments not affecting the outcome variables but affecting treatment. We create additional instruments for the probit model selection equation by inter-acting the two instruments mentioned above with all the covariates in the x_i vector in the outcome equations.

6. Results

6.1 Descriptive Statistics

Descriptive statistics for the treatment group (households that use services of and hold saving with SACCOs, but not MFIs, banks) and the control group (households that do not use services of SACCOs, banks and MFIs) are presented in Table 1 below. The table compares a number of selected demographic and socio-economic variables for the treatment and control cohorts before matching the data. The independent two-sample t-test is used to test for significant differences between the means of the selected variables. The results show statistically significant differences in the means of various covariates between the two cohorts before matching, such as such electricity use, household income, and value of assets, HDDS, FCS, household clothing and footwear expenditure, and school enrollment rates.

Table 1. Observable Characteristics of Treatment and Control Households - 2010/2011

Variable	Full Sample (N=1,917)	Non-SACCO HHs (N=1,734)	SACCO HHs (N=183)	t-value
Region - Kampala (yes=1)	0.054 (0.226)	0.053 (0.224)	0.060 (0.238)	-0.40 (0.688)
Region - Central (yes=1)	0.263 (0.440)	0.272 (0.445)	0.175 (0.381)	2.85*** (0.004)
Region - Eastern (yes=1)	0.262 (0.440)	0.264 (0.441)	0.240 (0.429)	0.69 (0.488)
Region - Northern (yes=1)	0.250 (0.432)	0.260 (0.439)	0.158 (0.366)	3.02*** (0.003)
Region - Western (yes=1)	0.171 (0.371)	0.151 (0.358)	0.366 (0.483)	-7.47*** (0.000)
Location (Urban=1)	0.177 (0.381)	0.171 (0.376)	0.235 (0.425)	-2.17** (0.030)
Electricity Use (yes=1)	0.079 (0.269)	0.073 (0.259)	0.138 (0.346)	-3.12*** (0.002)
Cook with Firewood (yes=1)	0.829 (0.377)	0.834 (0.373)	0.781 (0.414)	1.78* (0.075)
Cook with Charcoal (yes=1)	0.218 (0.412)	0.206 (0.405)	0.328 (0.471)	-3.80*** (0.000)
Married Monogamously (yes=1)	0.523 (0.498)	0.511 (0.500)	0.634 (0.483)	-3.17*** (0.002)
Married Polygamously (yes=1)	0.477 (0.498)	0.489 (0.500)	0.366 (0.483)	3.17*** (0.002)
Divorced (yes=1)	0.104 (0.305)	0.110 (0.313)	0.049 (0.217)	2.57*** (0.010)

Widowed (yes=1)	0.157 (0.364)	0.163 (0.370)	0.098 (0.299)	2.30** (0.022)
Single (yes=1)	0.026 (0.160)	0.026 (0.159)	0.027 (0.163)	-0.11 (0.914)
Household Head Sex (Male=1)	0.686 (0.463)	0.675 (0.469)	0.792 (0.407)	-3.27*** (0.001)
Household Head Age (years)	46.699 (15.819)	46.801 (16.112)	45.732 (12.701)	0.87 (0.385)
Household Head Education (years)	6.611 (3.747)	6.351 (3.723)	8.621 (3.926)	-7.41*** (0.000)
Household Head Work Experience (years)	21.739 (16.576)	22.056 (16.832)	19.164 (14.317)	2.15** (0.031)

Note. ***, **, * Indicates significance at 1%, 5%, and 10%, respectively. Standard deviations are in parenthesis for Columns 1,2,3. p-values are in parenthesis for Column 4. *Exchange Rate; US\$1.00 = Shs 2,200*

Table 1. Continued Observable Characteristics of Treatment and Control Households - 2010/2011

Variable	All Sample	Non-SACCO	SACCO	t-value
	(N=1,917)	HHs (N=1,734)	HHs (N=183)	
Household Size	6.863 (3.521)	6.700 (3.449)	8.404 (4.150)	-6.23*** (0.000)
Adult Equivalence	3.638 (2.061)	3.523 (1.999)	4.730 (2.580)	-7.54*** (0.000)
Household Total Dependents	3.372 (2.430)	3.285 (2.392)	4.197 (2.764)	-4.83*** (0.000)
Number of Houses Owned	1.153 (0.875)	1.144 (0.875)	1.235 (0.880)	-1.33 (0.183)
Value of Houses Owned (Shs)	3,253,836 (20,032,0)	2,421,718 (11,239,511)	11,124,852 (54,908,001)	-5.59*** (0.000)
No. of Commercial Buildings Owned	0.357 (0.903)	0.328 (0.847)	0.634 (1.323)	-4.35*** (0.000)
Value of Buildings Owned (Shs)	1,067,256 (14,767,7)	748,075 (11,996,083)	4,086,393 (30,384,444)	-2.91*** (0.004)
Value of Land Owned (Shs)	7,778,305 (33,165,5)	6,338,259 (22,531,026)	21,399,727 (82,037,190)	-5.84*** (0.000)
Total Income (Shs)	4,368,703 (20,437,2)	3,819,483 (20,780,153)	9,572,789 (16,825,370)	-3.62*** (0.000)
Value of Assets (Shs)	14,517,973 (67,922,9)	11,787,049 (55,748,161)	40,394,597 (137,660,81)	-5.42*** (0.000)

Income/Asset Ratio	3.717 (28.511)	3.886 (29.896)	2.122 (6.676)	0.80 (0.426)
Household Dietary Diversity Score (HDDS)	7.053 (2.528)	6.929 (2.546)	8.225 (2.348)	-6.58*** (0.000)
Food Consumption Score (FCS)	41.706 (18.528)	40.489 (18.467)	53.228 (19.090)	-8.82*** (0.000)
Household Clothing/Footwear Expenditure	88,688 (138,296)	77,361 (132,183)	189,247 (184,054)	-10.32*** (0.000)
School Enrollment Ratio	0.495 (0.347)	0.485 (0.351)	0.581 (0.311)	-3.46*** (0.001)

Note. ***, **, * Indicates significance at 1%, 5%, and 10%, respectively. Standard deviations are in parentheses for Columns 1, 2, 3. p-values are in parentheses for Column 4. *Exchange Rate; US\$1.00 = Shs 2,200*

6.2 Covariate Balancing for 2009/2010 and 2010/2011 Samples

The results of quality of matching or covariate balancing are shown in the Appendix. As expected, matching achieves a reduction in the standardized bias, the pseudo- R^2 , the likelihood ratio chi-square and the statistical significance of the likelihood ratio chi-square. The reduced pseudo- R^2 indicates that covariates have very low explanatory power for selection into the treatment group. The reduced statistical significance shown by the p-values of the likelihood ratio chi-square indicate that there are no systematic differences in the distribution of covariates between the treatment and control cases after matching. That is, the hypothesis that both cohorts have the same distribution in the covariates after matching cannot be rejected.

6.3 Impact of SACCOs on HDDS and FCS

Tables 2 and 3 show the results for the 2009/2010 and 2010/2011 samples. The results of the estimated ATT using the Epanechnikov Kernel matching algorithm are presented and are compared to those of the Nearest Neighbor and Radius matching algorithms. We also test for the endogeneity of assignment to treatment using the Wu-Hausman test and we reject the null hypothesis that assignment to treatment is exogenous. Thus we employ the two-step Treatment Effects Model (Switching Regression) that also explicitly controls for hidden selection bias and compare the results to those obtained using PSM. Table 2 shows that households that held savings with SACCOs have a higher mean household dietary diversity score (HDDS) than that of households with no contact with formal or semi-formal financial institutions. Thus access to SACCOs savings services has a positive effect on the household dietary diversity score (HDDS). The difference between the mean HDDS for the treatment group and the mean HDDS for the control group is statistically significant. The 2010/2011 sample shows when a household chooses to engage in SACCO savings services, on average, their HDDS increases by 11.70%. Similar results are obtained for the 2009/2010 sample, that is, HDDS increases by 10.70%.

Table 2. Impact of SACCOs on Household Welfare - Households in Sample of 2010/2011

Method and Outcome	ATT	t-value	Hidden Bias (Γ)	Number of Matched Pairs	No of Obs. Treatment Effects Model
HDSS					
Kernel Matching	0.876***	4.12	2.10†† 2.30†	155	
Nearest Neighbor Matching	1.006***	3.37	1.45†† 1.60†		
Radius Matching	0.894***	4.27	2.20†† 2.35 †		
Treatment Effects Model	0.976***	2.58	-0.550 ^a		1228
FCS					
Kernel Matching	8.565***	5.02	2.10†† 2.25 †	155	
Nearest Neighbor Matching	8.323***	3.60	1.70†† 1.80 †		
Radius Matching	8.845***	4.27	2.20†† 2.40 †		
Treatment Effects Model	8.200**	2.01	-0.540 ^a		1228
Clothing Expenditure (Shs)					
Kernel Matching	83,761***	5.00	1.75†† 1.90 †	154	
Nearest Neighbor Matching	88,306***	2.78	2.35†† 2.55 †		
Radius Matching	87,198***	5.25	1.90†† 2.05 †		
Treatment Effects Model	87,667**	1.77	-0.380 ^a		1228
School Enrollment Ratio					
Kernel Matching	0.088***	2.44	1.35†† 1.45 †	105	
Nearest Neighbor Matching	0.078**	1.89	1.20†† 1.30 †		
Radius Matching	0.087***	2.49	1.35†† 1.50 †		
Treatment Effects Model	0.113**	1.94	-1.00 ^a		1228

Note. ***, **, * indicate significance at 1%, 5%, and 10%, respectively. †† indicates the value of Γ at 5% level of significance. † indicates the value of Γ at 10% level of significance. ^a denotes the t-value for Lambda in the hazard function of the treatment effect model. *Exchange Rate; US\$1.00 = Shs 2,200*

Table 3. Impact of SACCOs on Household Welfare - Households in Sample of 2009/2010

Method and Outcome	ATT	t-value	Hidden Bias (Γ)	Number of Matched Pairs	No of Obs. Treatment Effects Model
HDDS					
Kernel Matching	0.804***	2.72	1.75 †† 1.95 †	94	
Nearest Neighbor Matching	0.894**	2.23	1.35 †† 1.50 †		
Radius Matching	0.770***	2.74	1.70 †† 1.90 †		
Treatment Effects Model	0.710**	1.93	0.280 ^a		605
FCS					
Kernel Matching	6.485***	2.61	1.35 †† 1.50 †	90	
Nearest Neighbor Matching	6.447**	1.91	1.20 †† 1.30 †		
Radius Matching	6.580***	2.77	1.40 †† 1.50 †		
Treatment Effects Model	6.427**	1.80	-0.550 ^a		605
Clothing Expenditure (Shs)					
Kernel Matching	92,666***	2.36	1.60 †† 1.75 †	94	
Nearest Neighbor Matching	124,210***	4.05	2.65 †† 2.95 †		
Radius Matching	91,316***	2.49	1.55 †† 1.70 †		
Treatment Effects Model	90,378**	2.19	-0.830 ^a		605

Note. ***, **, * indicate significance at 1%, 5%, and 10%, respectively. †† indicates the value of Γ at 5% level of significance. † indicates the value of Γ at 10% level of significance. ^a denotes the t-value for Lambda in the hazard function of the treatment effect model. *Exchange Rate; US\$1.00 = Shs 2,200*

The HDDS results in Tables 2 and 3 above are robust to whichever method of estimation that is used. Households who save and borrow from SACCOs have the flexibility of inter-temporal consumption smoothing thus can increase their dietary diversity. Food Consumption Score (FCS) captures both the quality and quantity of food consumed by households. The results shown in Tables 2 and 3 indicate that

households who held savings with SACCOs had higher mean Food Consumption Score (FCS) than that of the control group. The difference in the mean FCS between the two groups is statistically significant. That is, when a household chooses to engage in SACCO savings services, on average, their mean FCS increases by 19% due to inter-temporal flexibility in consumption smoothing opportunities provided by SACCOs. The results are consistent and robust to whichever method of estimation that is used.

The findings above are in tandem with those from randomized controlled trials done by Ksoll et al. (2016) for micro-savings in Malawi, by Beaman et al. (2014) in Mali and by Dupas and Robinson (2013) in Kenya. Ksoll et al. (2016) find, for Village Savings and Loan Associations (VSLAs) in Malawi that savings have a positive impact on consumption, as measured by number of meals consumed per day. Beaman et al. (2014) find, for community based savings group program that focused on women, in Mali that savings have a positive impact on food security. Dupas and Robinson (2013) find that savings in Kenya have positive impact on food expenditure, especially for market women. Van Rooyen et al. (2012) note that the findings of Dupas and Robinson (2013) suggest that increased household food expenditures can be linked to increased food quality. Household savings improve food security through increased food access. This is usually linked to the household's ability to purchase food or produce food. Zeller and Sharma (2000) argue that savings provide a pathway by which households accumulate capital to smooth consumption in difficult times. Inter-temporal consumption smoothing through savings helps households deal with income shocks or unexpected increases in expenditures. In Uganda vulnerable HHs self-insure against idiosyncratic risks across periods by holding precautionary savings in the form of relatively liquid assets (Kiiza & Pederson, 2006). Thus households that hold precautionary savings are able to adjust their income and consumption and in turn stabilize their food security through diet diversity, quantity and quality of food.

6.3 Impact of SACCOs on Household Clothing and Footwear Expenditure

The estimated impact of access to SACCO savings services on annual household clothing and footwear expenditure for the period 2010/2011 and 2009/2010 are presented in Tables 2, and 3 above; and Table 4 below. The difference between the mean annual household expenditure on clothing and footwear for the treatment and control group is about Shs 90,000 (US\$41). This difference is statistically significant. The results are consistent and robust to whichever method of estimation that is used. In Table 4 below we indicate that the mean household size of the treatment group is not statistically different from that of the control group after matching the data of the two cohorts. For instance, after Kernel matching, the mean household size for the control group in the 2010/2011 sample is 7.880. That of the treatment group is 8.351, the difference between the two means is not statistically significant, p-value = 0.272. For the 2009/2010 sample, the mean household size for the control group after matching is 7.533 and for the treatment group its 7.585 and p-value is 0.907. Therefore it cannot be argued that, on average, the treatment group household size was far greater than that of the control group which would explain the large difference in clothing and footwear expenditure between the two groups. This finding is consistent with the study by Dupas and Robinson (2013) who conducted a randomized control trial

(RCT) in Kenya for savings and find a positive impact on private expenditures, especially for market women. However, some studies that have used randomized evaluation methods find no statistically significant impacts of savings on non-food expenditures (Karlan et al., 2017; Beaman et al., 2014). For example, Karlan et al. (2017) find no impact of savings on non-food expenditures (such as transport, clothing, electricity, and petrol) for a clustered randomized evaluation spanning three African countries which include Ghana, Malawi, and Uganda. Our findings suggest that after controlling for household size and annual household income, treatment households spend more on clothing and footwear than the control households due to the inter-temporal flexibility in consumption smoothing opportunities provided by SACCOs.

Table 4. Clothing and Footwear Expenditure: Matched Household Size Means

<u>2010/2011 Sample</u>			
Method	Non-SACCO	SACCO	p-value
	HHs	HHs	
Kernel Matching	7.880	8.351	0.272
Nearest Neighbor Matching	8.214	8.351	0.736
Radius Matching	7.770	8.351	0.178
<u>2009/2010 Sample</u>			
Method	Non-SACCO	SACCO	p-value
	HHs	HHs	
Kernel Matching	7.533	7.585	0.907
Nearest Neighbor Matching	7.511	7.585	0.858
Radius Matching	7.510	7.585	0.867

6.4 Impact of SACCOs on Household School Enrollment Rates

The results in Tables 2 and 3 above show the estimated impacts of SACCOs on school enrollment rates for the two UNPS samples of 2010/2011 and 2009/2010. The enrollment rate is computed as the ratio of the sum of dependent children in primary, second and tertiary institutions to the total number of dependent children in the household. The average treatment effect on the treated using Kernel matching is 0.088 which is statistically significant. This finding suggests that households who hold savings with SACCOs have higher school enrollment rates than the control households and the difference is statistically significant. From these findings we posit that a household may have a life cycle motive whereby saving affords the household with the necessary capital for making investments in physical, human and social capital, which in turn generate more income, and thus making more money available for investment in education or human capital. Thus holding savings at SACCOs is expected to decrease the probability of being liquidity constrained across periods. This inter-temporal flexibility increases likelihood of marginal increments in long-term investments in education of children. We do not report

the results of SACCO impact on school enrollment rates for the UNPS of 2009/2010 because they are not significant.

6.5 Tests for Robustness of the Results

We test for robustness of the results using several methods. *First*, we check whether the results are robust to the method of estimation. We examine the impact of SACCOs on HDDS, FCS, household expenditure on clothing and footwear, and school enrollment rates. We run the propensity score matching method with different algorithms and also employ the two-step treatment effects method while controlling for hidden selection bias. In all cases the results are very similar. *Second*, following Rosenbaum (2002, 1987), we generate estimates of the magnitude of hidden selection bias that are necessary to invalidate the ATT study findings, that is, the parameter gamma Γ and check its value at 5% and 10% level of significance. The closer Γ is to the value of 1.0, the more sensitive the findings are to small amounts of hidden selection bias. In our study the lowest value of Γ is 1.20 at 10% level of significance (see Tables 2 and 3). We consider this a safe point that is far enough away from $\Gamma = 1.0$ to allay concerns about the influence of unobserved confounding on the ATT estimates. All the other estimates of Γ are far enough from 1.0 and indicate that our ATT estimates are not sensitive to hidden selection bias at 5% and 10% level of significance.

Third, we follow Jalan and Ravallion (2003, 1999) and test for potential remaining hidden selection bias due to confounding factors using the Sargan-Wu-Hausman test after matching the treatment and control groups using Nearest Neighbor matching. For all the results in Tables 2 and 3 above, we run an OLS regression of each outcome variable on the residuals from the probit selection equation, the propensity score, and a set of additional control variables that exclude the instruments used to identify exogenous variation in each of the outcome variable mentioned above. If the coefficient on the residuals is significantly different from zero, then hidden selection bias is still a problem even after matching the data. In all cases, we find that the coefficient on the residuals is not statistically significant even at 10% level. We can then assert that the impact estimator, ATT, is a result of participation in the treatment and hidden selection bias is not a problem. *Fourth*, we examine the coefficient of Lambda λ , the hazard function, in the two-step treatment effects model where hidden selection bias is controlled for. In all cases coefficient on λ is not statistically significant. This implies that hidden selection bias is not a problem when we estimate the impact of SACCOs on HDDS, FCS, household expenditure on clothing and footwear, and school enrollment rates using the treatment effects model.

7. Conclusions

Adequate financial inclusion of the poor in terms of formal financial institution services in Uganda, like in many other developing countries, is still a very big problem. Banks and traditional microfinance institutions have limited coverage. Thus there has been the development and growth of semi-formal channels of financial inclusion, such as SACCOs to bridge to this gap in financial inclusion. This study examines the impact of SACCOs on household diet diversity score; household food consumption score;

household clothing and footwear expenditure; and household school enrollment rates. Using data from the living standards measurement survey (LSMS) we employ the Propensity Score Matching (PSM) method and complement this with the two-step Treatment Effects (Switching Regression) Model to determine the impact of SACCOs on household welfare. We find that SACCOs have a positive and significant impact on household diet diversity score; household food consumption score; household clothing and footwear expenditure; and household school enrollment rates. The effect is statistically significant in all cases and the results are robust to the method of estimation. Tests show that confounding factors are not a serious problem in our average treatment of the treated (ATT) estimations. Our results show that SACCOs play a key role in improving: (i) household food security; (ii) some non-food household expenditures; and (iii) school enrollment rates. This is true for the poor households facing financial exclusion from banks and traditional microfinance institutions. These results have important poverty alleviation implications since SACCOs do not require substantial investment in physical and institutional infrastructure like that required to run formal microfinance organizations.

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APPENDIX 1: PSM Covariate Matching Quality for the 2010/2011 Survey Sample

	Un-Matched Sample			Matched Sample		
	Pseudo R^2	$p > \chi^2$	Mean Bias	Pseudo R^2	$p > \chi^2$	Mean Bias
HD DS						
Kernel Matching	0.167	0.000	23.435	0.010	1.000	5.346
Nearest Neighbor	0.167	0.000	23.435	0.050	0.621	9.243
Radius Matching	0.167	0.000	23.435	0.016	1.000	6.864
FCS						
Kernel Matching	0.167	0.000	23.435	0.010	1.000	5.346
Nearest Neighbor	0.167	0.000	23.435	0.050	0.621	9.243
Radius Matching	0.167	0.000	23.435	0.016	1.000	6.864
Clothing & Footwear Expenditure						
Kernel Matching	0.159	0.000	22.200	0.009	1.000	5.024

Nearest Neighbor	0.159	0.000	22.200	0.050	0.616	5.074
Radius Matching	0.159	0.000	22.200	0.015	1.000	6.407
School Enrollment Ratio						
Kernel Matching	0.191	0.000	19.544	0.029	1.000	7.398
Nearest Neighbor	0.191	0.000	19.544	0.038	0.997	8.625
Radius Matching	0.191	0.000	19.544	0.044	0.990	9.227

APPENDIX 2: PSM Covariate Matching Quality for the 2009/2010 Survey Sample

	Un-Matched Sample			Matched Sample		
	Pseudo R^2	$p > \chi^2$	Mean Bias	Pseudo R^2	$p > \chi^2$	Mean Bias
HDHS						
Kernel Matching	0.211	0.000	25.381	0.028	0.999	5.613
Nearest Neighbor	0.211	0.000	25.381	0.058	0.815	7.134
Radius Matching	0.211	0.000	25.381	0.028	0.998	5.873
FCS						
Kernel Matching	0.251	0.000	29.205	0.046	0.968	8.134
Nearest Neighbor	0.251	0.000	29.205	0.039	0.981	7.868
Radius Matching	0.251	0.000	29.205	0.062	0.836	10.479
Clothing & Footwear Expenditure						
Kernel Matching	0.211	0.000	25.381	0.028	0.999	5.613
Nearest Neighbor	0.211	0.000	25.381	0.058	0.815	7.134
Radius Matching	0.211	0.000	25.381	0.028	0.998	5.873