Village savings and loan associations and household welfare: Evidence from Eastern and Western Zambia

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Abstract

This study uses propensity score matching (PSM) and data from Eastern and Western Zambia to estimate the impact of participation in village savings and loan associations (VSLAs) on consumption expenditure among rural households. As a proxy for welfare, consumption expenditure is often argued to be more reliable and less prone to under-reporting errors than income. The results indicate large positive and statistically significant consumption effects of participation in VSLAs. As much as 38% and 17% of total and per capita weekly household expenditure respectively can be attributed to participation in VSLA interventions. This is consistent with most prior studies and seems to suggest that, if properly designed and implemented, informal savings and lending initiatives equally have the capacity to contribute to rural poverty alleviation by facilitating access to affordable credit through savings.

Key words: rural finance; VSLAs; welfare; Zambia

1. Background

FinScope surveys conducted between 2006 and 2007 indicate that the most striking contrast between Zambia and other countries in the region is its high proportion of people with no access to financial services. About 66% of adult Zambians are unserved by either formal or informal financial institutions. Poor access to financial services has traditionally been cited as a major impediment to the growth of the agricultural sector in Zambia. A high-risk economic and policy environment, expensive credit, low levels of agricultural risk assessment capacity within institutions, and poor financial literacy have all been cited as contributing to limited liquidity in agricultural markets. Poor and the rural population segments are often argued to suffer the greatest constraints, with approximately half the rural population financially excluded and only 26% said to be accessing formal financial products (FinScope 2015).

This situation has generated concern among policy makers and collaborating partners. To enhance access to finance among rural households, the Government of the Republic of Zambia (GRZ), through the Ministry of Finance (MoF), and the International Fund for Agricultural Development (IFAD) jointly designed and implemented the Rural Finance Programme (RFP) between 2007 and 2013. The RFP was implemented through a consortium of local non-governmental organisations (NGOs), micro-finance institutions (MFIs) and two government parastatals, the Development Bank of Zambia (DBZ) and the National Savings and Credit Bank (NSCB). The goal of the RFP was to improve rural livelihoods by increasing the use of sustainable financial services in rural areas.

The RFP had five components, one of which was the development of community-based financial institutions (CBFIs), which focused on increasing the number and capacity of CBFIs in rural areas.[1] The development of CBFIs was aimed at improving the access of commercially active poor rural households to community-based financial services through the promotion of rural self-owned and managed institutions. To attain this overall goal, the programme contracted CBFI promoters, consisting of NGOs and MFIs, to support and facilitate the establishment of 2 500 self-owned and self-managed village savings and loan associations (VSLAs), each with up to 10 to 20 active members. The contracted CBFI promoters developed methodologies, including testing promising modifications and piloting more advanced systems, with a continuous focus on savings mobilisation.

Although MFIs have provided financial services to millions of people over the last few decades, access in rural areas remains a major challenge (Brannen & Sheehan-Connor 2012; IPA 2015). Despite the recent explosive growth in microfinance globally, most MFIs have an urban orientation (Allen & Panetta 2010; Demirgüç-Kunt & Klapper 2012). With a poor road network and lower population density in rural areas, it is costly for MFIs to reach the rural poor (Brannen & Sheehan-Connor, 2012; IPA 2015; VSL Associates 2015). There also is a gap between the products that MFIs offer and those that are needed by the poor. For instance, while MFIs stress credit, it is savings that improve household cash-flow management and are a better fit for this clientele, which prefers to minimise risk by limiting its exposure to debt (VSL Associates 2015). Traditional community methods of saving, such as rotating savings and credit associations (ROSCAs), can provide an opportunity to save, but they do not allow savers to earn interest on their deposits as a formal account would. In addition, ROSCAs do not provide a means for borrowing at will, because although each member makes a regular deposit to the common fund, only one lottery-selected member can keep the proceeds from each meeting (IPA 2015). One intervention that has gained increased popularity in rural Africa is savings groups. Savings groups provide an alternative to existing informal networks (ROSCAs) and provide more flexibility, transparency and security. One highly standardised type of savings groups is a VSLA (Ksoll *et al*. 2016).

VSLAs attempt to overcome the difficulties of offering credit to the rural poor by building on the ROSCA model to create groups of people who can pool their savings to have a source of lending funds (IPA 2015). In a VSLA, members make savings contributions to the pool, and can also borrow from it. VSLAs are built entirely on member savings and interest rates from the loans. Members, however, do receive a year of intensive training in group governance and money management, which allows them to become self-sufficient and even enables them to establish other groups (Brannen & Sheehan-Connor 2012). The activities of the group run in cycles of one year, after which the accumulated savings and the loan profits are distributed back to the members. The purpose of a VSLA is to provide simple savings and loan facilities in areas which do not have easy access to formal financial services.

[1] The four other components are: (i) promotion of rural banking services, which focused on improving the outreach and quality of service of formal banks in rural areas; (ii) credit facilities for contracted small-scale production, which focused on credit delivery to contracted smallholder farmers and the out-grower companies they work for; (iii) innovation and outreach (I&O) facilities, which supported the development and up-scaling of sustainable and appropriate rural finance operations and encouraged financial institutions to develop new pro-poor financial products and services; and (iv) policy, institutional and management support, which ensured effective programme implementation.

As a self-sustaining and self-replicating mechanism, VSLAs have the potential to bring access to financial services to remote areas (Brannen & Sheehan-Connor 2012; IPA 2015). However, empirical evidence of the impact of VSLAs on household welfare remains scarce. Although several studies have looked at the welfare effects of VSLAs within southern Africa and elsewhere (Brannen & Sheehan-Connor 2012; Deresse & Calfat 2013; Ksoll *et al*. 2016), very few have been designed to measure the impact of VSLA participation in a scientifically robust way, and none in Zambia. An initial impact evaluation of the RFP in Zambia at the end of the programme in 2013 found higher welfare levels when measured in terms of both income and expenditure among treatment households. However, this study did not disaggregate the five different programme components and their corresponding interventions, and thus did not quantify the size of impact for each intervention component. Rigorous impact studies are a valuable source of lessons for subsequent intervention design and implementation.

This study uses propensity score matching (PSM) and data from Eastern and Western Zambia to estimate the impact of participation in village savings and loan associations (VSLA) on consumption expenditure among rural households. To the best of our knowledge, this study represents the first comprehensive treatment of the impact of VSLA interventions on household welfare in the country and region. Brannen and Sheehan-Connor (2012) recently completed an impact evaluation of the VSLAs in Tanzania, while Ksoll *et al.* (2016) evaluated the impact of VSLAs in Northern Malawi. Our paper contributes to this new literature in the region. Most prior studies have used income as a proxy of welfare. We use consumption expenditure as the outcome variable. As a proxy for welfare, consumption expenditure is often argued to be more reliable and less prone to under-reporting errors than income (Meyer & Sullivan 2003). The results indicate large positive and statistically significant consumption effects of VSLA participation. As much as 38% and 17% of total and per capita weekly household expenditure respectively can be attributed to participation in VSLA interventions. This is consistent with the findings of Ksoll *et al*. (2016) and Annan *et al*. (2013), and seems to suggest that properly designed informal savings and lending initiatives equally have the capacity to contribute to rural poverty alleviation by facilitating access to affordable credit through savings.

The rest of the paper is organised as follows. Section 2 presents a brief overview of VSLAs in Africa and Zambia. The conceptual framework, on which the empirical models were based, is presented in Section 3. Section 4 presents the methods and procedures, followed by the empirical results in Section 5, and the summary and conclusions in Section 6.

2. Village savings and loan associations in Africa and Zambia

The VSLA model was developed by CARE International in Niger in 1991 and has spread to at least 61 countries in Africa, Asia and Latin America, with over six million active participants worldwide (VSL Associates 2015).[2] The inspiration for VSLAs came from ROSCAs (Ksoll *et al*. 2016). The aim has been to improve on ROSCAs in several respects: i) to make the groups more sustainable through a series of accountability features that prevent the theft of funds and elite capture (Ksoll *et al*. 2016); ii) to make them more flexible, as members can at any time borrow the amount they want up to three times their own level of savings if funds are available (Brannen & Sheehan-Connor 2012; Ksoll *et al*. 2016); and iii) to encourage savings and investments among low-income community members. Unlike in ROSCAs, borrowers in VSLAs pay interest on loans to the group, which should

[2] In Africa, the VSLA methodology has been implemented in Angola, Benin, Burkina Faso, Burundi, Cameroon, the Central African Republic, Chad, Ivory Coast, the Democratic Republic of the Congo, Egypt, Eritrea, Ethiopia, Ghana, Guinea, Guinea Bissau, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mali, Mozambique, Niger, Nigeria, Rwanda, Senegal, Sierra Leone, Somalia, South Africa, Sudan, South Sudan, Swaziland, Tanzania, Togo, Uganda, Zambia and Zimbabwe.

encourage more savings by those with greater means while simultaneously discouraging borrowing for less productive purposes (Brannen & Sheehan-Connor 2012).

Whereas ROSCAs multiply without external facilitation, VSLAs only do so to a limited extent, thus requiring the facilitation of, say, an NGO, perhaps due to reasonably complex accountability features (Ksoll *et al*. 2016). After conducting awareness meetings in every targeted village, the promoting agency facilitates the formation and training of groups. Initially, groups are visited every week in the first three months to set up the procedures. Groups work as a member-owned financial intermediary with three products – savings, credit and insurance. Savings are compulsory and are collected at the weekly meetings and conceptualised as buying shares. Every week, a member must buy at least one share and is permitted to buy up to five. The share value is set by the group and written in the group's constitution (Ksoll *et al*. 2016; Allen & Staehle 2007). In our case, a share was equivalent to ZMW 10.00 in most areas (in 2013).[3]

Loans are provided at every fourth meeting. If the funds requested by members exceed the amount of saved funds, the group decides who gets the loan by following a predetermined list of criteria written in the group's constitution. The interest rate on loans is set by the group (Klonner 2008). In the case of Zambia, most groups were charging between 10 and 30% interest on the borrowed money. Loan contracts run for three months, with a grace period of one month. Rules for loan approval are set in the group's constitution (Ksoll *et al*. 2016). A group never fines borrowers for late loan repayment, as this may aggravate any underlying crisis the household may be facing. It is assumed that the embarrassment of being late is sufficient penalty (Allen & Staehle 2007).

The overall interest rate on savings is typically four to five percent per month, but materialises only after the end of a cycle, typically lasting around 12 months, when all savings and interest payments are divided by the number of shares and paid out (Brannen & Sheehan-Connor 2012; Rasmussen 2012). The overall interest rate on savings is lower than the interest on loans because not all the funds are lent out all the time and savings accumulate over time. The actual date of the final share-out is set by the group and tends to be chosen according to the period when most households need cash, in order to encourage the use of savings to meet pressing needs and to discourage their use for unnecessary expenditures (Brannen & Sheehan-Connor 2012; Ksoll *et al*. 2016). At the end of a cycle, members decide whether to leave or remain in the VSLA group and whether the group should accept new members (Ksoll *et al*. 2013). Given that the survey was undertaken in September 2013 and the VSLAs were established in 2009 and 2010, any impact found in our analysis is drawn from at most four full cycles of collecting savings, giving out loans and returning the savings with interest by the groups.

3. Conceptual framework

Traditionally, VSLAs are motivated by the extreme lack of savings and loan facilities in rural areas. In the case of extreme poverty, where households do not have the capacity to access credit from formal institutions for productive purposes, VSLAs are viewed as self-managed and capitalised microfinance methodologies that can alter the development equation in marginalised communities worldwide, providing members with the means to cope with emergencies, build capital and re-create social dynamics that support genuine self-reliance (IPA 2015).

Under the RFP implemented in Zambia, VSLAs were targeted at improving the access of commercially active rural households to community-based financial services through the promotion of rural self-owned and managed institutions. Thus, the most anticipated effect of VSLAs is increased welfare levels in the immediate term, but with long-term implications for productivity. The idea is

[3] The average exchange rate in Zambia in 2013 was ZMW 5.3 = USD 1.00

that increased access to credit through savings could increase households' economic activities, as well as discourage unnecessary expenditure, and hence reactivate their latent potential to further improve their welfare. Specifically, by providing access to affordable and readily available credit, VSLAs can help households acquire key agricultural inputs. In addition to credit, by discouraging unnecessary expenditure, VSLAs have been found to enable households to improve their capacity to afford essential items, such as food, health services and school fees.

One of the most reliable measures of welfare in the literature is consumption expenditure. Although expenditure and income are supposed to be equivalent, the latter tends to be volatile and prone to under-reporting bias. This makes consumption-based measures more informative as welfare indicators than income (Meyer & Sullivan 2003). Thus, we use consumption expenditure as a proxy for welfare in our analysis.

Ksoll *et al*. (2016) found VSLAs to have a positive impact on household consumption and other welfare indicators among participants in Malawi. In Tanzania, Brannen and Sheehan-Connor (2012) found long-term VSLA-participating households to be better along multiple nutritional and health dimensions compared to a control of recent joiners. Similarly, Annan *et al*. (2013) found the impact of VSLAs on several welfare indictors in Burundi to be impressive.

Identification of impact

Programme impacts are measured by assessing whether a programme changes the mean value of an outcome variable among participants compared with what the outcome would have been had they not participated. Thus, programme impact is defined as the expected value of the difference between the level of the outcome variable attained by participating households and that which they would have attained had they not participated in the programme (Ravallion 2001; Wooldridge 2002). That is:

$$ATT = E(Y_{1i} - Y_{0i} \mid w_i = 1) \tag{1}$$

where ATT is the average treatment effect on the treated, Y_{1i} is the weekly total or per capita consumption expenditure (our outcome variables of interest) of the treatment group (households that participated in the VSLA interventions), Y_{0i} is the weekly total or per capita consumption expenditure of the comparison group, w_i is a dichotomous variable equal to one if the household participated in the VSLAs and zero otherwise, and $E(.)$ is the expectations operator.

Weekly consumption expenditure was computed by adding together the values of all food items consumed by the household (whether purchased or own-produced) during the week prior to the survey. Equation (1) represents the conditional mean impact, conditional on participation, also known as the treatment effect or the average treatment effect on the treated (ATT) (Wooldridge 2002). However, the central evaluation problem is that participants cannot be simultaneously observed in the alternative state of no participation, referred to as the counterfactual (Shahidur *et al*. 2010). If there is a difference in the mean of the outcome variable between participants and non-participants in the absence of the programme, a bias will arise, and this bias is given by:

$$b = E(Y_{0i} | w_i = 1) - E(Y_{0i} | w_i = 0) \tag{2}$$

This bias could be corrected if $E(Y_{0i} \mid w_i = 1)$ were known. Unfortunately, the level of participants' consumption expenditure had they not participated in the intervention cannot be observed. However, had the programme been assigned randomly, the participants and non-participants would have the same expected consumption expenditure in the absence of the programme. In this case, the expected consumption expenditure of non-participants will correctly reveal the counterfactual. A key feature of experimental design is complete randomisation, which ensures that households in the treatment and control groups are similar and that any observed systematic differences in the outcome variable are attributable to the intervention. However, complete randomisation is not always possible in observational studies such as ours (Becker & Ichino 2002). For most projects and programmes, complete randomisation is not possible due to ethical, cost and other pragmatic reasons (Becker & Ichino 2002). In the case of the implemented VSLAs, treatment households either self-selected themselves and/or were deliberately chosen based on their individual characteristics. Thus, since the assignment of subjects to the treatment and control groups is mostly non-random in observational studies, the estimation of the effect of treatment may be biased by the existence of confounding factors (Becker & Ichino 2002). Under such a quasi-experimental design, statistical controls must be used to address differences between the treatment and control groups (Barker 2000). Evaluators typically simulate the counterfactual by comparing programme participants with a control with similar characteristics. Construction of the counterfactual determines the evaluation design, which is broadly classified as experimental or quasi-experimental. Ravallion (2001; 2003) has characterised the various methods used to estimate impact under quasi-experimental conditions. As a second-best alternative for these conditions, comparison can be facilitated by statistically constructing comparable treatment and comparison strata. Under some form of exogeneity (Imbens 2004), most quasi-experimental impact studies estimate the conditional average treatment effect on the treated as:

$$ATT = E(Y_{1i} - Y_{0i} \mid \mathbf{x}, w_i = 1) \tag{3}$$

where $\mathbf{x}$ is a vector of covariates or explanatory variables. The assumption implied by equation (3) is that conditioning on carefully selected covariates renders the household's treatment status independent of potential outcomes, such that the unobserved $E(Y_{0i} \mid w_i = 1)$ can be represented by the observed $E(Y_{0i} \mid w_i = 0)$. This makes it possible to attribute any systematic differences in the outcome variables between treated and control units with the same values of the covariates to the programme in question. A more dimensionally appealing but equivalent version of 'selection on observables' involves replacing $\mathbf{x}$ in Equation (3) with the estimated conditional probability of participation, or propensity score, defined as $\hat{p}(\mathbf{x}) = E(w = 1 \mid \mathbf{x})$ (Rosenbaum & Rubin 1983). Rosenbaum and Rubin (1983) show that, if exposure to treatment is random within the cells defined by the covariates $\mathbf{x}$, it is also random within cells defined by the values of the one-dimensional propensity score variable $\hat{p}(\mathbf{x})$. Thus, given a population of units denoted by i, if the propensity score $p(x_i)$ is known, then the *ATT* that measures the impact of participation can be estimated as follows:

$$ATT = [E\{Y_{1i} \mid w_i = 1, p(x_i)\} - E\{Y_{0i} \mid w_i = 0, p(x_i)\} \mid w_i = 1] \tag{4}$$

Propensity score matching (PSM) is a way to correct the estimation of treatment effects controlling for the existence of confounding factors based on the idea that the bias is reduced when the comparison of outcomes is performed using treated and control subjects who are as similar as possible. Since matching subjects on an n-dimensional vector of characteristics are typically infeasible for large *n*, PSM summarises the pre-treatment characteristics of each subject into a single-index variable (the propensity score) that makes matching feasible (Becker & Ichino 2002). We used the propensity score procedure to estimate the impact of VSLA participation on household welfare in Eastern and Western Zambia.

Propensity scores allow us to balance the distributions of the covariates between treatment and control households based on the similarities of their predicted probabilities of participating in VSLAs (Mendola 2007). This is because controls in the covariates have different distributions for their participation status. As such, allowing VSLA participation to interact with other covariates, and then comparing welfare variables between treatment and control households, would be a "wild-goose chase", since we would be comparing incomparable things. PSM handles this problem of "comparing the incomparable" perfectly, since it makes no assumptions about the functional form of the impact. By restricting impact evaluation to local comparisons where the counterfactual is quite similar in characteristics to the treatment group, we find that it is not very far from what we would observe if households were randomly assigned to the two subgroups (treatment and control).

4. Methods and procedures

4.1 Data and data sources

This study uses cross-sectional survey data from the Kaoma and Mongu Districts in the Western Province, and Chipata, Katete and Petauke Districts in the Eastern Province of Zambia, where VSLAs were implemented under the RFP. The survey was conducted between September and October 2013 by the Institute of Economic and Social Research (INESOR) of the University of Zambia (UNZA) under contract to and with support from the Zambian Ministry of Finance (MoF) and the International Fund for Agricultural Development (IFAD). A total sample of 313 treatment and 185 comparison households (that is, households located in the same neighbourhood as the treatment households but with no members participating in VSLAs) was drawn using multi-stage stratified random sampling. The selection of treatment households was based on a sampling frame developed from a register of households participating in VSLAs compiled by CBFI promoters, whereas the sampling frame for the comparison households was developed through comprehensive listing of control households within the same neighbourhood. First, clusters (participating CBFI promoters) were randomly selected from an exhaustive list of all CBFI promoters. Second, study districts and communities were randomly selected under each selected cluster (CBFI promoter). Finally, households in selected districts and communities were randomly included in the sample using proportional-to-size sampling. Although the households in the two strata looked similar on the basis of visible characteristics, we also used matching techniques to ensure comparability.

4.2 Empirical models

4.2.1 Estimation of the propensity scores

Propensity score matching (PSM) presents a unique set of techniques for reconstructing an experimental environment from non-random, quasi-experimental conditions. Following Becker and Ichino (2002), we used variants of propensity score-based estimators to estimate the impact of VSLAs on household consumption expenditure, where the propensity scores (PS), or conditional probabilities of participation, were estimated using a probit specification:

$$\text{Prob}(w=1|\mathbf{x}) = \Phi(\theta + \boldsymbol{\delta}'\mathbf{x} + \varepsilon) \tag{5}$$

where Φ is the standard normal cumulative distribution function (CDF), ε is an error term, θ is the intercept to be estimated, $\boldsymbol{\delta}$ is a vector of slope parameters, also to be estimated, and $\mathbf{x}$ is a vector of covariates. Equation 5 was estimated using maximum likelihood (ML) procedures in Stata.

When using PSM, we mimicked a randomised experiment so that we could evaluate causal inference, as in a controlled experiment. For this to happen, we required the conditional independence assumption. This assumption states that, given a set of observable covariates x that are not affected by the treatment, potential outcomes Y are independent of treatment assignment w (Shahidur *et al.* 2010). That is, given Y_{1i} and Y_{0i} as defined above, the conditional independence assumption is defined as:

$$(Y_{1i}, Y_{0i}) \perp (w_i \mid x_i) \tag{6}$$

Equation (6) implies that participation in VSLAs is as a result of observable household characteristics, or the covariates. This is what Rosenbaum and Rubin (1983) call the unconfoundedness assumption.

To ensure consistency of PSM, only covariates that exhibited significant correlation with the participation variable and/or the outcome variable were included in x. Propensity score-based models are only as good as the quality of the matching and are valid only under certain identifying assumptions. The balancing effects of the propensity scores were tested using several procedures, including stratification, *t* tests for the differences in covariate means between participants and non-participants before and after the matching (Rosenbaum & Rubin 1985), effectiveness in reducing standardised bias, and ability to drive the overall probit relationship to insignificance as measured by a joint likelihood ratio (LR) test and pseudo R^2 (Caliendo & Kopeinig 2008).

4.2.2 Estimation of impact

After estimating equation (5), we used variants of the matching estimators of the *ATT* that are based on the propensity score. An estimate of the propensity score is not enough to estimate the *ATT* of interest using equation (4), because the probability of observing two units with exactly the same value of the propensity score is in principle zero, since $p(\mathbf{x})$ is a continuous variable (Becker & Ichino 2002). Various methods have been proposed in the literature to overcome this problem, and the four most widely used propensity score-based estimators of impact are nearest-neighbour matching, radius matching, kernel matching, and stratification matching estimators. Although the process of matching the treated with the control with comparable characteristics is achieved differently by each of these four estimators, all estimators involve, for each treatment unit, finding matches in the control group based on observable characteristics (Abadie & Imbens 2008). We used the kernel matching estimator to measure the impact of VSLA participation because it allowed all treatment households to be matched with a weighted average of all controls with weights that are inversely proportional to the distance between the propensity scores of the treated and the controls. Kernel matching, unlike nearest-neighbour matching, arguably leads to more valid bootstrapped standard errors (Gilligan & Hoddinott 2007; Abadie & Imbens 2008). That is, *ATT* was computed as the weighted average of the difference in the outcome variable between treatment households and matched control ones, where matching was done by kernel functions and *ATT* computation was restricted to the region of common support. The kernel matching estimator is given as (Smith & Todd 2005; Gilligan & Hoddinott 2007):

$$ATT = \frac{1}{n}\sum_{i \in T}\left\{ Y_{1i} - \frac{\sum_{j \in C} Y_{0j} K\left(\frac{P_j(\mathbf{x}) - P_i(\mathbf{x})}{a_n}\right)}{\sum_{k \in C} K\left(\frac{P_k(\mathbf{x}) - P_i(\mathbf{x})}{a_n}\right)} \right\} \tag{7}$$

where *T* is the treatment group participants, *C* refers to the comparison group, *K* is the kernel function, and a_n is the kernel bandwidth. Inferences were made possible by bootstrapping standard errors. To confirm the robustness of the impact results, we also employed the nearest-neighbour matching estimator to further evaluate the impact of VSLA participation on welfare.

5. Results and discussion

Table 1 presents selected characteristics of the sampled households. In general, the results indicate that the two sub-samples were generally well balanced with respect to most demographic variables (age and education level of household head, and household size). The balancing results in Table A1 show that the methods used to match treatment households with comparable control households were effective, based on the *t* tests for the differences in covariate means between participants and non-participants before and after the matching, and on the movement of the overall probit relationship from significance (p-value = 0.000) to significance (p-value = 0.994). The propensity score (PS)-balancing test results confirm the existence of strong bias for most covariates in the model before matching, and that balancing successfully eliminated this bias. In general, matching produces consistent estimates, as long as unobserved factors are equally distributed between the two groups. The estimated PS was also inspected for the common support requirement. This was found to be satisfied, as indicated by the fact that $0 < PS < 1$ and by the large PS overlap (0.235, 0.995) between the control and treatment households (Figure A1).

In contrast, with respect to economic and welfare variables (annual borrowing, consumption expenditure, agricultural production and wealth indices), the post-intervention descriptive results show that treatment households were on average better off than their control counterparts, suggesting a positive impact of VSLA participation. Not only did the treatment households have a greater wealth index, but they also had more livestock, as indicated by a positive livestock index. Treatment households were also recording higher agricultural yields and had the most consumption compared to the control households.

Table 1: Descriptive characteristics

Variable name	Variable description	Overall	Control units	Treated units
		(1)	(2)	(3)
Variable	Number of observations	498	185	313
hsex	Male-headed households (hh) (%)	70.10	70.27	69.97
hage	Age of hh head	45.40	42.98	46.82***
hhsize	Household size in 2013	5.58	5.18	5.82***
Hedu	Education level of the head (years)	6.37	5.58	6.83***
Hborrow	Annual hh borrowing (ZMW)	605.54	124	890.20***
hhcons	Weekly hh consumption expenditure	113.44	86.92	129.11***
$maizeprod_t$	Maize production in current agric. season (kg)	1,617.39	1,227.38	1,855.89***
$maizeprod_{t-1}$	Maize production in last agric. season (kg)	1,966.89	1,520.15	2,233.95***
windex	Asset wealth index	0.01	-1.16	0.70***
lindex	Livestock ownership index	-0.01	-0.26	0.13***

Source: Field survey, 2013

Notes: Test of statistical significance of mean differences between treatment and control/comparison households: *** p < 0.01, ** p < 0.05, * p < 0.1. Asset wealth and livestock indices were computed with principal component analysis, as in Filmer *et al*. (2001).

The descriptive statistics were confirmed by the probit results of participation in VSLAs (

Table **2**). The marginal effects show that, among the treatment households, there were 15.6% more female-headed households than male-headed households. Similarly, the probit results show that marginal increases in the age and education level of the household head, asset and livestock indices, and agricultural production (proxied as maize yields in the 2011/2012 and 2012/2013 agricultural seasons) were associated with an increase in the household's probability to participate in VSLA interventions.

Table 2: Propensity score estimation with the probit model

Variable	Variable description	Parameter estimates	Marginal effects
		(1)	(2)
cons	Intercept	-0.329 (0.314)	
Hsex	Sex of hh head (1 = male and 0 = female)	-0.441*** (0.158)	-0.156*** (0.053)
hage	Age of hh head	0.018*** (0.005)	0.007*** (0.002)
hedu	Education level of the head (years)	0.032* (0.019)	0.012* (0.007)
Windex	Asset wealth index	0.173*** (0.033)	0.064*** (0.012)
Lindex	Livestock ownership index	0.189** (.076)	0.070** (0.028)
Maizeprodt	Maize production in current agric. season (kg)	2.51e-05 (3.54e-05)	-9.34e-06 (1.0e-05)
maizeprod_{t-1}	Maize production in last agric. season (kg)	3.60e-05 (5.16e-05)	1.34e-05 (2.0e-05)
Number of observations		423	
Likelihood ratio Chi-sq		77.31***	
Pseudo R^2		0.1380	

Source: Field survey, 2013

Notes: Dependent variable: whether household participated in village savings and loans associations (VSLAs) (= 1) or not (= 0). Standard errors in parentheses. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Impact estimates

The descriptive statistics discussed earlier indicate that treatment households were relatively better-off, as indicated by production, wealth and consumption. However, descriptive statistics are limited and may not imply causality, as they fail to quantify and later on to account for other sources of the observed differences. Table 3 presents the impact of participation in VSLA interventions on household welfare, proxied as weekly total and per capita household consumption expenditure. Both PSM estimators (nearest-neighbour matching and kernel matching) indicate large positive effects of VSLA participation. Using the kernel-based matching estimator with bootstrapped standard errors replicated 100 times, we find that participation in VSLA interventions raises weekly total household expenditure by 19.8% and weekly per capita household expenditure by 17.77%. These results are significant at the 1% level of significance. To verify the robustness of the results from the kernel-matching estimator (attk), we employed the nearest-neighbour matching estimator (attnd) after estimating the propensity score equation. The results from the nearest-matching estimator confirm the results from the kernel estimator, namely that participation in VSLAs has an unambiguous, positive effect on household welfare.

Table 3: Impact estimates based on propensity score matching

Welfare variable	Variable description	ATT estimates using kernel estimator (attk)	ATT estimates using nearest-neighbour estimator (attnd)
HHCONS	Weekly total household expenditure	0.198*** (0.051)	0.384*** (0.050)
Number of observations		498	498
Treated households		264	313
Control households		146	185
PCHHCONS	Per capita weekly household expenditure	0.177*** (0.051)	0.152* (0.080)
Number of observations		498	498
Treated households		264	264
Controls households		146	90

Source: Field survey, 2013

Notes: Standard errors in parentheses. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. In all impact estimation models, the balancing property was satisfied and the common support option was imposed.

6. Conclusions

Several factors have been cited for the low welfare levels in Zambia, among them low production and hence lower household incomes. Lack of access to credit and finance have often emerged as important obstacles to increased production. The encouragement of savings groups is seen by many as an alternative to solving the limited access to credit and financing among poor households with no collateral to use if they are to borrow from formal credit institutions. This study examined the impact of VSLA participation on household welfare. The results, based on the two PSM-based impact estimators, show the existence of significant and positive consumption effects. On average, as much as 19 to 38% of weekly total household expenditure, and 15 to 17% of weekly per capita household expenditure, could be attributed to the households' participation in VSLA interventions. As the finance sector is undergoing structural transformation, from being small and largely informal to large and formal, with links to established institutions, these results suggest that properly designed informal savings and lending initiatives could still play an important role in facilitating access to affordable credit through savings. During data collection, several treatment households revealed that the intervention (VSLAs) allowed them to save even smaller amounts, a development they claimed reduced their unnecessary expenses. This is somewhat contrary to conventional, and largely anecdotal, arguments, namely that poor households lack meaningful resources among themselves and thus that access to credit can only be possible through external sources. This therefore calls for the re-orientation of public sector support and emphasis being shifted from the enhancement of only formal and contract farming financing to a mix of strategies that also include ways to promote savings among households as a way of creating local capital for investments. For example, the incorporation of savings in the cooperative societies formed largely to enable rural households to access fertiliser subsidies from the government could eventually lead to increased savings, and hence more local capital for investment by households.

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A1. Balancing properties of covariates in treated and control groups

Variable	Sample	Mean treated units	Mean control units	% bias between treated and controls	% reduction in $\lvert\text{bias}\rvert$	H_0: mean (treated) = mean (control) t Probability $> \lvert t \rvert$	
		(1)	(2)	(3)	(4)	(5)	(6)
Hsex	Unmatched	0.670	0.703	-0.700		-0.070	0.943
	Matched	0.724	0.719	1.200	-89.100	0.140	0.889
Hage	Unmatched	46.817	42.989	28.100		3.010	0.003
	Matched	45.654	46.003	-2.600	90.900	-0.290	0.771
Hedu	Unmatched	6.840	5.578	33.200		3.570	0.000
	Matched	6.387	6.281	2.800	91.600	0.320	0.749
maizeprodt	Unmatched	2233.9	1520.2	24.100		2.370	0.018
	Matched	2128.4	1950.1	6.000	75.000	0.620	0.539
maizeprod_{t-1}	Unmatched	1855.9	1227.4	28.300		2.790	0.005
	Matched	1700.8	1583.0	5.300	81.300	0.650	0.516
windex	Unmatched	0.697	-1.163	68.000		7.170	0.000
	Matched	0.189	-0.006	7.100	89.500	0.900	0.368
Lindex	Unmatched	0.129	-0.259	39.600		4.260	0.000
	Matched	0.227	0.2100	1.700	95.700	0.190	0.848

Note: Matching reduced pseudo R^2 from 0.138 to 0.002 and the overall likelihood ratio for the probit relationship from 77.31 (p-value = 0.000) to 1.05 (p-value = 0.994).

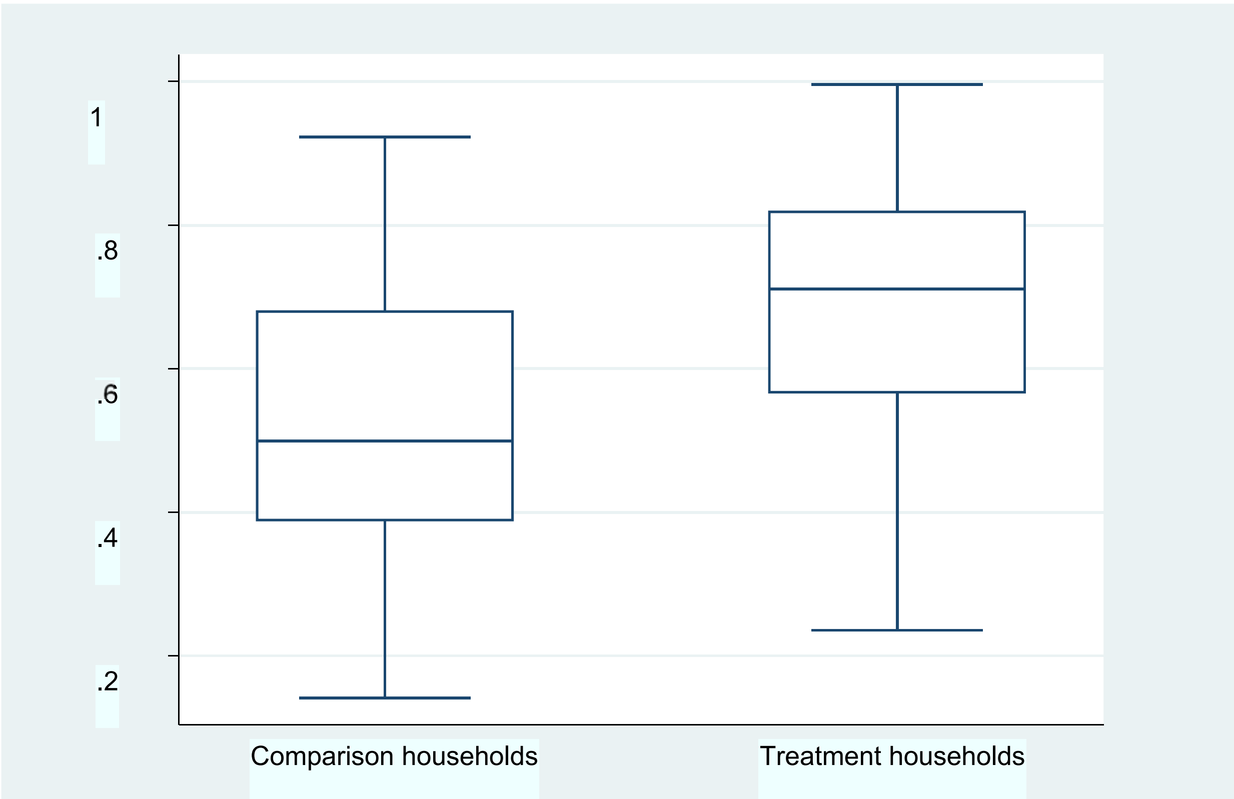

Figure A1. Distribution of propensity scores over comparison and treatment households. Note: Common support requirement was satisfied within (0.235, 0.995).