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Full Length Research Paper

The nexus between access to credit and farm income: A propensity score matching approach for smallholder dairy farmers in Central Kenya

James Sidika[1*], Martin Muriuki[2], Yusuf Tande[3]

[1]Department of Agricultural Bio systems, Economics and Horticulture, University of Kabianga, Kericho, Kenya.
[2]Department of Agriculture and Environmental studies Rongo University.
[3]Department of Agriculture and Environmental Studies, Rongo University, Rongo, Kenya.

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Abstract

In this contemporary economic system characterized by rapid population increase, more food is required to encounter the ever growing food demand. Adequate credit accessibility and utilization therefore becomes necessary to achieve a sustained level of production and income. In view of this, we examined the link between access to credit and farm Income in Kinangop Sub-County in the Central Highlands of Kenya. Descriptive survey research design was employed on a target population of 35,840 dairy farm households. Similarly, cross-sectional data was collected from a sample of 230 smallholder farmers using both stratified and simple random sampling techniques. Descriptive analysis involved running a t test and chi square tests to compare the means and frequency distribution of different variables respectively while inferential statistical methods involved the propensity score matching technique to determine the average treatment effects. Descriptive methods revealed significant differences in respondents gender, ownership status, financial education status, association membership status and value addition practice. Significant differences in income characterized by gender, financial education status, association membership status and value addition practice were also observed. In addition, milk output, off-farm income, on-farm income; ($p \leqslant 0.01$), land size, land under forage production; ($p \leqslant 0.05$) and number of associations;($p \leqslant 0.01$) were significantly higher for credit users relative to credit non-users. Estimation of the Average Treatment Effect revealed a positive and significant effect of credit access on farm income with credit users having their income increased by between KES 6,307.5 and KES 7,358.5. Enhancing credit accessibility is therefore vital in increasing income returns of dairy farmers.

Key words: credit, farm income, smallholder dairy farmers, propensity score matching, kinangop.

INTRODUCTION

Globally, milk production accounted for 659 million tons of fresh cow milk, six percent coming from Africa (Food and Agriculture Organization, 2018). East Africa producing 68 % of the continent's milk output (Bingi and Tondel, 2015) and 43 % of cow milk.Kenya's annual dairy milk output was estimated at 3.8 billion litres which accounted for 76 % of total cattle milk (Kibogy, 2016).According to Kenya National Bureau of Statistics.
KNBS (2020) Kenya's milk output was approximately 7 litres per cow per day with only 15 % being formally marketed and 84 % being for consumption and for the informal marketing system. Annual per capita milk consumption stood at

121 litres against a production of approximately 6 litres per cow (Kenya Dairy Board, 2017). This implies that domestic milk supply is still unable to meet the growing demand for milk, thus, widening the gap between demand and supply. Central Kenya region comprises approximately 800,227 exotic and 325,678 indigenous cattle (KNBS, 2018). In Nyandarua County, dairy farming is still the major economic activity comprising: Friesian, Guernsey, Jersey and the Ayrshire as the major livestock breeds majority of farmers preferring the Friesian breeds (Nyandarua County Integrated Development Plan, 2018). In Kinangop Sub County there are a total of 35,690 dairy cattle. The region produced 86,510,200 litres of milk in 2018 which is approximately 7 litres/cow/day (Kinangop Sub County Livestock Production Office, 2018).

The area has commercial banks, different dairy cooperatives societies, and micro finance institutions, different Non-Governmental Organizations focusing on the provision of agricultural credit, private money lenders and various government credit schemes such as Uwezo Fund, Youth Funds and Women Enterprise Fund all of which were established to enhance credit accessibility in the region (NCIDP, 2018). Moreover, improved access to financial services facilitates acquisition of farm inputs and the relevant technologies which can be used in the production process (Negissie & Ndinda, 2017). According to International Development Authority(2019), only 4 % of formal sector credit goes to the agribusiness sector despite the immense contribution of the sector to the economy. Similarly, given limited evidence available for Kinangop Sub County, this study has generated empirical evidence on how access to credit relates to dairy farm income in the region. The study was therefore guided by the following objectives.

Research Objectives

1. To determine the socio-economic characteristics of credit users and credit non-users in Kinangop region.
2. To find the effect of access to credit on farm income among smallholder dairy farmers in Kinangop region.

LITERATURE REVIEW

Overview of the credit market in Kenya

In the recent past, Kenya has experienced an increase in the number of credit institutions such as Banks, Micro-Finance Institutions and various Savings and Credit Co-operatives. However, Kenya's rural financial services are still not well developed due to lack of comprehensive financial strategies (Kariuki, 2016). On the contrary, Msati and Kamau (2015) asserts that there has been a massive evolution of the financial system in Kenya characterized by growth of institutional set up which has been facilitated by an equally developing information technology. The credit market in Kenya is categorized into three major groups namely: formal, semi-formal and informal sectors. The formal sector being supervised by the Central Bank of Kenya and it comprises banks and non-bank financial institutions, such as investment houses, insurance companies, financing companies and security markets (Owuor and Shem, 2012).

The sector is characterized by a set of complex administrative and lending procedures and often display little interest in smallholder agricultural financing (Osano & Languitone, 2016). The main users of formal financial sector are large scale enterprises with economies of scale. Kenya has witnessed an improvement in access to formal financial services (Central Bank of Kenya, 2019). From the report, an additional 7.6 % of SMEs were included into the formal sector borrowing from the period 2016-2019 an indication of progress. However, Ellen (2016) highlighted the failures in the formal sector towards meeting the credit needs of small and medium enterprises. Their study asserts that high interest rates, preference for large loan volumes makes it difficult to accommodate small and micro enterprises. United States Aid for International Development (2018) observed low levels of credit access among smallholder farmers despite existence of diverse formal credit providers. Farmers being locked out due to unfavorable terms. This gave rise to the semi-formal credit service providers. They comprise institutions that are not regulated by the banking act but are registered and licensed by the Government to provide loans(Central Bank of Kenya, 2019). Some of the institutions include the Agricultural Finance Corporation (AFC), Savings and Credit Co-operatives, Microfinance Institutions (MFI) and Non-Governmental Organizations (Owuor and Shem, 2012).Informal credit sources are also on the rise and are greatly preferred due to their favorable terms.

This scheme comprises non-institutional and unregulated credit services providers that take place outside the functional domain of the formal financial sector regulations (Sile & Bett, 2015). Their rules and regulations emanate from the local cultural context and constitute small groups such as Savings and Credit Cooperatives (SCC), Savings and Credit Associations (SCA), grain millers, employers, Rotating Savings and Credit Associations (ROSCAs)

Accumulating Saving and Credit Associations (ASCRAs), Mutual Assistance Groups (MAGs) and individuals such as friends, relatives and money lenders (Sile & Bett, 2015). An impressive attribute of informal financial markets is the relaxation of collateral barriers and lower interest rates. The informal finance therefore exists due to the inefficiencies within the formal credit markets (Sile & Bett, 2015). Informal lenders are heavily attracted to the borrower's character and loan history (Jalil, 2015).

Contribution of Credit Accessibility in Enhancing Agricultural Income of Farmers

Ibrahim and Bauer (2013) conducted a study on access to micro credit and its impact on farm profits among rural farmers in Sudan and found credit users to be better off with higher level of profits than credit non-users. (Abate & Agerwork , 2022) applied the propensity score matching approach to evaluate the impact of access to micro credit on farm income and expenditure in Ethiopia. From their study results access to micro-credit improved farm household income by 207.7 USD for the treated farmers. Similar results were obtained by (Chigizie and Ambrose, 2013), from their findings, credit access had a positive impact on household welfare. Reyes *et al.,* (2013) assessed the impact of access to short term credit on farm productivity of fruit and vegetable growers in Chile for market-oriented farmers. The study however revealed that short-term credit does not have an impact on farm productivity, while other factors as education and the type of activity significantly influenced farm productivity. The study recommended that other providers of credit, such as informal credit institutions, may relax short-term credit constraints in rural financial markets in Chile so as to enhance accessibility and credit amount. Aboidun et al., (2018) reported a significant impact of access to credit on farm income in Lesotho; through the propensity score matching procedure, income of credit users was improved by between 100 to 137 USD.
From the literature review, it is clear that there exist knowledge gaps in regards to the application of the propensity score analysis to evaluate the effect of access to credit on dairy farm income in Kinangop region. Most studies focused on the effects of credit access on SMEs and farm households in general without specific consideration to smallholder dairy farmers in Kinangop Sub County (Abate & Agerwork , 2022)**.**

Study Area

The study area was Kinangop Sub County within Nyandarua County in Central Kenya. Major crops grown are irish potato, cabbages, french beans, snow peas. Since the area is elevated, it has abundant tree cover which forms thick forests with thick undergrowth supported by well drained soils. Night frosts are also common in the area. Similarly, the area experiences an annual rainfall of between (1100-2700) mm. Livestock fodder (grass), timber, poles and fuel wood are the main forest products forming part of both gazatted and non-gazetted forests. The major trees grown are cypress, pine and eucalyptus some of which act as alternative sources of income for farmers. The area has commercial banks and various micro-finance institutions nevertheless, there is still need to increase income earning opportunities through commercializing agriculture, and enhancing access to capital and credit facilities (NCIDP, 2018). The site has been selected since it is the main dairy production zone in Nyandarua County. Similarly, smallholder farmers were considered due to their varied scale of production as well as their dominance in the area. Friesian is the main livestock breed, other breeds include: Guernsey, Jersey and Ayrshire. The area has eight wards, twenty-two sub locations and an area of 934.7sq. Km

Sample Size and Sampling Procedure

According to Nassiuma (2000) the sample size is given by: $n = \frac{\mathrm{NC}^2}{\mathrm{C}^2+(\mathrm{N}-1)\mathrm{e}^2}$ Where: n = sample size, N = Study population given as 35, 840, C = Coefficient of variation and e is the error term. Taking the coefficient of variation of 0.30 and a standard error of 0.02, we obtain a sample size of 230 respondents. Stratified sampling technique was used to group farmers based on wards. Thereafter, asimple random sampling technique was used to proportionately select the final subjects from each stratum as presented in Table 1

Data and Data analysis

Structured questionnaires administered by the researchers were used to collect quantitative data related to various socio-economic characteristics, income and farm demographics. The collected data was inputted into STATA version 13 software and analyzed using both descriptive and inferential statistical methods. In descriptive analysis chi-square and student t-tests were run to provide insights on the mean and frequency distribution of the data set.

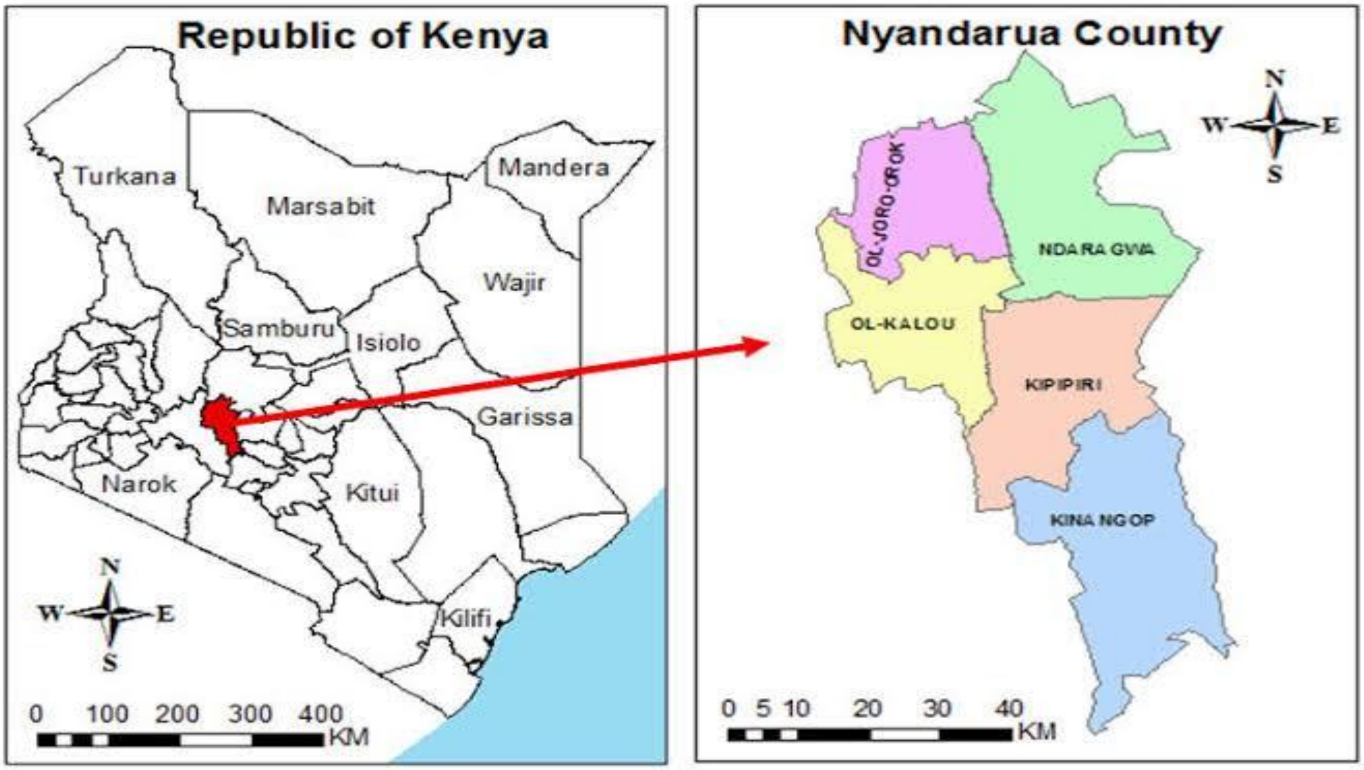

Figure 1. Map of Kenya locating the study area.

Table 1. Sample size determination.

Ward	Population (P)	Sample size (P/T)n
Engineer	4,659	30
Njabini	3,942	25
Magumu	2,150	14
Nyakeo	5,376	35
Murungaru	6,093	39
Gedhabai	4,301	27
Gadhara	4,309	28
North Kinangop	5,010	32
TOTAL (T)	35, 840	230

Inferential statistical modelling involved running aPSMATCH2 command to estimate the average treatment effect on the treated.

Methodological Framework

One approach to estimating income differentials between credit users and credit non-users is by using the standard t-test. One limitation of this method is its failure to account for selection bias leading to biased results. The issue can be confronted by using before and after analysis in which income before the intervention is used as a baseline scenario against which current levels of income are evaluated. However, due to absence of panel data, it proved difficult to generate a baseline scenario. The study therefore relied on cross-sectional data obtained from the respondents. The question was therefore, how to create a suitable counterfactual situation (control group) to provide a basis for comparing outcomes. In order to address this problem, propensity score approach was used. PSM creates a counterfactual group where there is no random assignment (Abiodun et al., 2022). PSM heavily relies on two important assumptions; the conditional independence assumption and the balancing condition. The CIA assumption requires that the outcome should be independent on treatment status. The balancing condition requires an overlap in the covariates of both the treated and control groups (Caliendo and Kopeinig, 2008).

Econometric Specification

This study statistically models two important aspects of credit, credit involvement among smallholder dairy farm households and consequently the magnitude of income derived conditional on access to credit. This particular scenario steers a propensity score matching procedure. Previous studies have also applied the model for similar circumstances (Abiodun et al., 2022; Abate & Agerwork, 2022). Given that treatment is typically dichotomous (i.e., *D*=1 for the treated and *D*=0 for untreated units) and since PSM is a conditional probability estimator, any binary outcome model would be suitable in the first step. For this study, a binary logit model was used to estimate the propensity scores for both the treatment and control groups. In a regression framework, the treatment effects model is given by

$Y_{ij} = YD_i + X_i \lambda + \varepsilon_{ij}$ (1)

Where Y_{ij} is net farm income, X_i is the vector of explanatory variables, D_i is the dummy variable for credit access (1= credit user, 0 = credit non-users), ε_{ij} = Random disturbance term. The second step involved matching each credit user to a credit non-user with similar propensity score. Nearest Neighbor Matching algorithm with replacement was employed in matching. In "with replacement", an untreated individual was used more than once. This was to increase the average quality of the matching and to reduce the level of biasness. The third step involved conducting a balancing test to establish whether the differences in the treatment group (credit users) and control group (credit non-users) have been eliminated so as to consider the matched comparison group as an acceptable counterfactual (Adjin et al., 2020).

The rationale is that the distribution of the covariates between the treatment and control groups should be the same after matching (Rosenbaum and Rubin, 1983). A reduction in the pseudo R2 and Chi2 values after matching indicates a reduction in bias. Similarly, an insignificant p-value of the likelihood ratio test indicates absence of systematic differences in the distribution of covariates between the two groups after matching.The fourth step involved estimation of the effect of the intervention. In estimating the effect, the common support region was identified. This area consists of positive balancing scores for both the treatment and comparison groups (Caliendo and Kopeinig, 2008). The common effects identified include the Average Treatment Effect (ATE), Average Treatment Effect on the Treated (ATT) and the Average Treatment Effect on the Untreated (ATU). The ATT measures the average impact of the intervention on the treated units whereas the ATU measures the average impact of the intervention on the control units had they been treated. The ATE measures the average impact of the intervention on the entire sample. The three effects were specified as:

$ATE = E [E \{Y_{1i} /D_i = 1, P (Z_i)\} – E \{Y_{0i} /D_i = 0, P (Z_i)\}]$ (2)

$ATT = E [E \{Y_{1i} /D_i = 1, P (Z_i)\} – E \{Y_{0i} /D_i = 0, P (Z_i)\}/D_i = 1]$ (3)

$ATU = E [E \{Y_{1i} /D_i = 1, P (Z_i)\} – E \{Y_{0i} /D_i = 0, P (Z_i)\}/D_i = 0]$ (4)

Where: Y_{1i} and Y_{2i} are the outcomes of credit users and credit non-users respectively. D_i is a binary dependent variable, where D_i = 1 is the value for participants farmers and D_i = 0 is the value for non-credit users. Z_i Are the characteristics of the i^{th} Smallholder dairy farmer, $P(Z)_i$ is the propensity scores for each Smallholder dairy farmer. Finally, a sensitivity analysis was conducted using the Rosenbaum bound test (r-bound test) to check the effect of any hidden biases on the estimated treatment effects and these biases occur when there are unobserved variables which affect the inclusion into treatment group and the outcome variable (farm income) at the same time (Caliendo *et al.,* 2008). When these hidden biases occur, there will be need to measure the variables and include them in the matching and the treatment effects estimated. This can influence the significance of the effect and may make the results not robust. The r-bound is used to test the null hypothesis indicating no change on the treatment effect for different values of unobserved selection bias hence not deciding whether or not hidden biases exist as well as magnitude of the biases (Rosenbaum and Rubin, 1985).

Theoretical Framework

The study was grounded on the rational choice theory developed by Glasser (1998). According to the theory, individuals rely on rational decisions to achieve optimum outcomes. A huge potential exists when a household is a credit user and consequently, smallholder dairy farming households who exploit this potential are expected to be well-off in terms of welfare gains (income). The decision to be a credit user relies on each farmer's self-selection rather than random assignment and is driven by the expected higher utility. Although we cannot directly observe utility, smallholder dairy farmers' actions are observed through the choices they make. For instance, if we assume that U_j and U_k represent a household's utility choices for being a credit user and for being a credit non-user, which are denoted by Y_j and Y_k respectively. The linear random utility model could then be specified as:

$$u_j = \beta_j X_i + \varepsilon_i \quad (5)$$

$$u_k = \beta_k X_i + \varepsilon_k \quad (6)$$

where U_j and U_k are perceived utility choices for being a credit user and a credit non-user, *j* and *k*, respectively, X_i is the vector of explanatory variables that influence the perceived desirability of each choice, β_j, and β_k are utility shifters (coefficients), and ε are error terms assumed to be independently and identically distributed (Greene, 2000). The differences in utilities between credit users and credit non- users is therefore specified as

$$L_i = X_{IJ}\alpha + V_I \quad (7)$$

Where: L_i is the latent variable that illustrates the difference between utility derived from being a credit user and utility derived from being a credit non-user. Hence the decision of being a credit user required the satisfaction of the following condition $L_i = U_C - U_J > 0$. The welfare effect of being a credit user was then modeled as follows

$$Y_{ij} = X_i\lambda + YD_i + \varepsilon_{ij} \quad (8)$$

Where Y_{ij} is farm income, X_i is the vector of explanatory variables, D_i is the dummy variable for credit access (1= credit user, 0 = credit non-user), ε_{ij} = Random disturbance term.

RESULTS AND DISCUSSIONS

Proportion of credit users and credit non-users defined across categorical variables

From table 2, the number of credit user male headed households is greater than the credit users of female household heads. The difference was significant at 1% probability level an indication that more male headed households accessed credit than their female counterparts. These findings are consistent with the submissions of (Chandio *et al.,* 2017; Sekyi, 2017) and contradicts with the findings by (Dlamini and Mohammed, 2018). These studies posit that women are asked to provide additional collateral in order to access loans and since males have direct ownership of household resources in the rural set-up, they are likely to overcome collateral barriers.

Differences were also observed in regards to ownership types between credit users and credit non-users. 33% of credit users and 67% of credit non-users were sole traders while 62% of credit users and 38% of credit non-users were in partnership. The difference was statistically significant at 5% probability level an indication that more sole traders accessed credit than farmers who engaged in partnerships form of management. This could be attributed to the fact that since sole proprietors enjoy the independence of monopoly, they are likely to peruse their own financial strategies independently without undue obstruction and influence and as such will find it relatively easier to meet their credit needs.

The Number of dairy farm households who received financial training was higher for credit users than for credit non-users. Out of the total respondents, 62 % of credit users and 38 % of credit non-users were financially literate. In addition, 89 % of credit non-users never received financial training, only 11 % of credit users never received financial education. The difference in access to financial training between credit and credit non-users was statistically significant at 1 % probability level (Table 2). Training equips farmers with the necessary financial skills and brings forth more awareness on different financial products, procedures and the associated terms hence farmers are able to make decisions based on the available information (Siwale 2018)

In terms of membership to associations, 74 % of the association members were credit users while 26 % were credit non-users. Similarly, only 12 % of non-association members were credit users while 88 % of non-association members were credit non-users. The difference in membership to associations between credit users and credit non-users was statistically significant at ($p \leq 0.01$) which is in agreement with the findings of (Lemessa and Gemechu, 2016). Group members can easily overcome guarantor ship requirements by acting as co-borrowers. Consequently, groups also offer short term credit in form of table banking repaid within the regulations stipulated by their constitution hence the reason why more association members are credit users.

Further results reveal that a greater proportion of value adders were credit users, 56 % relative to 44 % of non-value adders who were credit non-users. Only, 31 % of non-value adders accessed credit whereas 69 % of non-value

Table 2. Proportion of credit users and credit-non users defined across categorcal variables.

Variables	Response categories	Credit users	Credit Non-users	χ2 value
Gender	Male	61(45)	76(55)	15.5639***
	Female	18(19)	75(81)	
Ownership type	Sole trader	71(33)	146(67)	4.5175**
	Partnerships	8(62)	5(38)	
Financial education	Yes	65(62)	40(38)	65.061***
	No	14(11)	111(89)	
Association membership	Yes	62(74)	22(26)	91.3813***
	No	17(12)	129(88)	
Value addition practice	Yes	19(56)	15(44)	8.2049**
	No	60(31)	136(69)	

Percentages in parentheses, ***, **,: significant at 1%, 5% respectively. Source: survey data (2021).

Table 3. Income differences across categorical variables.

Variable	Type	Mean income (s.d)	Mean Difference
Gender	Male	11,329.9 (6,826.2)	2,710***
	Female	8,619.4 (4,246.6)	
Business Ownership	Sole trader	10,135.0 (4,903.1)	1,749.6
	Partnership	11,884.6 (8,361.1)	
Financial education	Yes	13,005.7 (7,336.6)	5,100***
	No	7,905.6 (3,263.8)	
Association member	Yes	13,889.3 (7,458.1)	5,758.5***
	No	8,130.8 (3,730.8)	
Value addition	Yes	12,635.3 (8,102.1)	2,817.9**
	No	9,817.3 (5,550.2)	

Significance level: ***, **: significant at 1%, and 5%, respectively. Source: survey data (2021).

adders never accessed credit. The difference in value addition between credit users and credit non-users was statistically significant at ($p\leq0.05$).

Income differentials across categorical variables

From the descriptive results presented in Table 3, male headed households recorded significantly higher levels of income KES (11,329.9) than their female headed counterparts KES (8,619.4) ($p\leq0.01$). Since more male headed households are at the fore front in terms of credit programs than their female counterparts they have a competitive edge in terms of benefiting from trainings and access to credit which is likely to enhance their income returns (Jijal, 2014). Financially trained farmers had more income KES (13,005.7) than their counterparts KES.

(7,905.6) ($p\leq0.01$). This could be attributed to the fact that training provides new knowledge and skills essential in enhancing decision making ability of farmers hence more-able to leverage more resources to meet the production targets. As such, their income is likely to be improved.

Association members' recorded higher income levels KES (13,889.3) than non – association members KES (8,130.8). Associations create a platform for social networking where members can easily share knowledge and skills regarding new technologies in farming which is likely to translate into more output and income (Jijal, 2014).

Summary statistics for household credit users and non-users.

The descriptive summary of the respondents' socio-economic profile is presented in Table 4. On average, dairy farmers produced (341.1) litres of milk with credit users producing relatively more milk (531.27) litres than non-credit

Table 4. Summary statistics for household credit users and non-users.

Variable	Credit Users	Credit non-users	Pooled	Mean Difference
Milk output	531.27	241.66	341.1	289.61***
	(230.49)	(74.97)	(201.92)	
Off-farm income	17159	10235	12613.5	6924.4***
	(16174.1)	(9429.5)	(12577.9)	
On-farm income	15937.9	7249.7	10233.9	8688***
	(6914.5)	(2249.1)	(6057.6)	
Total land size	2.21	1.8	1.94	0.41**
	(1.02)	(1.07)	(1.14)	
Forage production	0.93	0.75	0.81	0.18**
	(0.64)	(0.55)	(0.59)	
No. of associations	2.4	1.2	1.6	1.24***
	(1.1)	(0.6)	(0.9)	

Source survey data (2021), ***,**: significant at 1%, and 5% respectively, standard deviations in parentheses.

users (241.66) litres. The difference (289.6) litres was statistically significant at ($p \leq 0.01$). These findings are in agreement with the findings of Sebatta *et al.,* (2014). In their study, finance borrowers recorded more annual crop output than finance non-borrowers.

Dairy farming households earned on average (KES 12,613.5) from off farm activities; credit users earning more (KES 17,159) than non-credit users (KES 10,235). The difference of (KES 6,924) was statistically significant at ($p \leq 0.01$). This indicates that credit users had more diversified income sources. These results show that respondents had low levels of off-farm income. FAO (2015) revealed low levels of off-farm income among smallholder farming households in Kenya. From their findings, smallholding households in Kenya generated on average USD 2,527 per annum which translates to approximately KES 25,000 per month. This study therefore attributes low levels of off-farm income to low level of diversification in the study area. Further analysis revealed that Smallholder dairy farmers earned a mean income of (10,233.9 KES) from on-farm activities; credit users earning more incomes (15,937.9 KES) than credit non-users (7,249.7 KES). The difference of (8,688KES) was statistically significant at ($p \leq 0.01$). This suggests that credit access is critical in enhancing farm income.

From the results in Table 4, the average land holding size is 1.94ha credit users having significantly larger portions (2.21ha) than credit non-users (1.80ha). The difference (0.41ha) was statistically significant at ($p \leq 0.05$). On average dairy farming households allocated (0.81ha) for forage production with credit users allocating relatively larger portions (0.93ha) than credit non-users (0.75ha). The difference of (0.18ha) was statistically significant at ($p \leq 0.05$). In regards to number of associations, credit users had an average membership of two associations whereas credit non-users had an average membership of one association; the difference was statistically significant at ($p \leq 0.01$) indicating a possible correlation between number of associations and credit access.

Summary of logit model results

The logit model was applied to estimate the propensity scores for each treated and control group. The outcome indicates that access to credit was significantly influenced by seven variables; marital status, years of formal education, savings, and dairy farming as a primary occupancy, financial literacy, membership to an association and number of dairy cattle as presented in table 5.

Distribution of the Propensity Scores

The mean average of the propensity score was 0.34 (Table 6) an indication that a randomly selected dairy farmer in the study area was 34.35 % likely to be a credit user. Consequently, the range of the propensity scores was between 0 and 1. This was achieved through identification of a common support region which validates the quality of the matches by removing propensity scores of the treatment group that are beyond the range of the propensity scores of control group.

Table 5. Logit model estimates of the covariates.

	Estimates		
Credit access	**Coef.**	**Std. Err.**	**Z**
Gender of respondent	1.1497	1.0949	1.05
Age of respondent	0.0240	0.0747	0.32
Marital status	0.8439*	0.5028	1.68
Household head	-0.9106	1.1791	-0.77
Years of schooling	0.2205*	0.1165	1.89
Size of household	-0.5015	1.2976	-0.39
Farming Experience.	-0.0753	0.1143	-0.66
Savings frequency	2.2349**	1.1417	1.96
Formal job	2.1518*	1.3041	1.65
Off farm Income	-2.2E-05	4.14E-05	-0.53
Ownership form	-2.6774	1.9583	-1.37
Financial training	2.5223**	1.0045	2.51
Association membership	1.5431*	0.8731	1.77
Value addition practice	-0.3335	1.3023	-0.26
land size	-0.3479	0.4586	-0.76
No. of dairy cattle	3.3450***	0.7400	4.52
_cons	-14.223	4.5695	-3.11
Number of obs =	230.00		
LRchi2 (18) =	238.76		
Prob>chi2 =	0.000		
Log likelihood =	-29.07		
Psuedo R2 =	0.8068		

Table 6. Sum of propensity score.

Variable	Obs	Mean	Std. Dev.	Min	Max
_pscore	230	0.34348	0.4361	0.0000589	1

Balancing Condition

From Table 7, the Pseudo R2 has been reduced and the Likelihood Ratio test is insignificant. This indicate that both credit users and credit non-users have the same distribution of covariates after matching i.e matching of the socio-economic characteristics of farmers in the study area has reduced the level of bias of the characteristics of credit users and credit non-user group. N5 reduced bias most compared to other matching algorithms as indicated by a greater reduction in mean bias after matching.

Impact Estimates based on the Treatment Effects

Table 8 presents the impact estimates from the propensity score matching technique.Nearest neighbour matching up to the fifth neighbour was used in estimating the average treatment effect. Results from N1 were however, not reported since it never satisfied the balancing condition.The ATT from the four matching algorithms were positive and significant at ($p \leq 0.01$) an indication that credit users were better off in terms of welfare gains (net-farm income) relative to credit non-users. The ATT ranged from was KES 6,307.5toKES 7,358.5 and were positive and statistically significant at ($p \leq 0.01$) an implication that utilization of credit increased farm income. These findings are in agreement with the findings of(Abate & Agerwork , 2022). From their studies, credit users earned more income from farming

Table 7. Evaluating matching quality.

Matching	Sample	Ps R2	LR chi2	p>chi2	Mean Bias	Median Bias
N 2	Unmatched	0.804	237.94	0.000	63.20	36.9
	Matched	0.24	12.59	0.634	24.00	22.5
N 3	Unmatched	0.804	237.94	0.000	63.20	36.9
	Matched	0.232	12.21	0.663	23.30	22.8
N 4	Unmatched	0.804	237.94	0.000	63.20	36.9
	Matched	0.24	12.59	0.634	24.00	22.5
N 5	Unmatched	0.804	237.94	0.000	63.20	36.9
	Matched	0.174	9.14	0.870	22.10	16.5

Source survey data (2021).

Table 8. Impact estimate on farm income.

Matching	Sample	Treated	Controls	Diff.	S.E.	T-stat
N2	ATT	14,835.	8,527.5	6,307.5***	2,150.8	2.93
N3	ATT	14,835.	7,995.	6,840***	1,954.6	3.5
N4	ATT	15,938.	8,579.4	7,358.5***	1,669.8	4.41
N5	ATT	14,835.	7,581.	7,254***	1,742.5	4.16

*** Significant at 1%, N; Nearest Neighbor Matching; Source survey data (2021).

Table 9. Results from the sensitivity analysis.

Γ	1	2	3	4	4.25	5	6
p-value (upper bound)	0.01	0.01	0.03	0.06	0.06	0.08	0.11
t-hat+	6,600	3,956	3,225	2,663	2,475	2,213	1,763
p-value (lower bound)	0.01	0.01	0.01	0.01	0.01	0.01	0.01
t-hat-	6,600	8,663	9,975	10,725	10,725	11,456	12,056

t-hat+ - upper bound Hodges-Lehmann point estimate

t-hat- - lower bound Hodges-Lehmann point estimate

Γ (log odds of differential assignment due to unobserved factors)

Source survey data (2021).

than credit non-users. This study finding could be explained by the fact that credit users were more-able to meet their investment obligations hence could leverage more opportunities for the advantage of production.

Sensitivity Analysis

The results of the Rosenbaum sensitivity analysis are presented in Table 9. The critical values of Γ bearing the statistical difference between credit users and credit non-users are presented in columns. When Γ = 1 the assumption of no hidden bias due to an unobserved confounder holds indicating a significant effect of credit access on farm income. The upper bounds are used to assess whether there is a positive selection bias which occurs when farmers with a higher probability of being credit users tend to have more income even without being credit users given similarity in their characteristics with credit non-users. This effect creates an upward bias in the estimated treatment effects. From the results, a 0.25 increase in Γ from 3 to 4 increases the p-values (upper bounds significance

significance level) to 0.06, a value above the 0.05 threshold. Similarly, when Γ is increased from 5 to 6 the p-value becomes insignificant. This means that, if the odds of being a credit user are 6 times higher due to unobserved covariates our inference will change. In conclusion, despite access to credit having a positive treatment effect the fi value is however, sensitive to possible hidden bias due to an unobserved confounder.

CONCLUSIONS AND RECOMMENDATIONS

In conclusion, the smallholder dairy farming system in Kinangop Sub County is still constrained as a result of in adequate access to financial services. Similarly, due to land fragmentation challenges, farmers allocated less acreage for production of fodder crops. Further results indicate significant variations in regards to milk output, off-farm income, on-farm income, landholding size, land under forage production and number of associations between credit users and credit non-users. Significant variations in income based on farmer socio-economic profiles such as gender, association membership, value addition practice and form of business ownership was also observed. Even though loan access had a positive effect on farm income, the impact was however minimal.

These results have potential usefulness in regards to policy. Firstly, since various socio-economic dynamics have a direct bearing on farm income, it would be prudent for credit service providers to develop loan products that are aligned to the needs different cadres of farmers. Through this, farmers are likely to select the most suitable loan products for resource optimization. Secondly, more emphasis should be given to gender inclusive credit policies where more female heads are included within the rural financial landscape. The policy should consider empowering more women with the pre requisite financial skills to enhance informed decision making. Thirdly, association membership and milk value addition practice have been found to boost income returns. Policy should focus on enhancing participation in group activities such as table banking and different value addition initiatives such as yoghurt making among others. Finally, there is need to enhance farmer financial literacy through many ways. One major way is that credit providers together with other stakeholders need to align financial literacy aspects in their training curriculum to the current challenges n dairy farming or establish adult literacy centers for purposes of adult education on financial and entrepreneurial aspects.

Conflicts of interest

The authors have not declared any conflict of interests

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