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Original Research Article

Impact of Participation in Milk Processing on Smallholder Farmers' Welfare: The Case of Kikima Dairy Cooperative Society in Makueni County, Kenya

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Abstract: The productivity of the few established cash crops in Makueni County is affected by low rainfall reliability, which in turn leads to drought and crop failure. Thus, the dairy sector is a crucial source of livelihood for the residents in Makueni County. The dairy sector, however, is constrained by the lack of adequate processing capacity which has the potential to enhance the shelf life and retail price of milk. It's for this reason that the Kikima dairy plant was established to provide a ready market for farmers' milk and enhance the processing capacity within Makueni County. However, there is scanty empirical evidence on the impact this dairy plant has had on farmers' welfare. The current study assessed the impact of participation in milk processing on farmers' welfare in Makueni County using farm income as the welfare indicator. The study used primary data with a sample size of 200 respondents drawn from Mbooni and Kilome sub-counties in Makueni County. The respondents were stratified by participation and farmers were randomly selected from the two sampling frames to give a sub-sample of 100 project participants and 100 non-participants. Data were then analyzed using descriptive and inferential statistics. The endogenous switching regression model was used to analyze the impact. The results indicated a negative impact of participating in milk processing on farmers' income.

Keywords: Endogenous Switching Regression Model, impact, milk processing, participation, smallholder farmer.

1.1 INTRODUCTION

The growing consumer demand for livestock products due to population growth is changing livestock systems globally (Willer *et al*., 2013). According to UN Report (2016), the African population is projected to increase to about rj64.4 billion by the year 2100. Consequently, this will lead to an increase in the demand for milk (Holechek *et al*., 2017) and the per capita consumption of fresh dairy products by an average of 1.9 percent per annum (FAO, 2019). In Kenya, the per capita consumption of milk is estimated to be 110 litres (SMP, 2018). The dairy industry in Kenya contributes to about 17 percent and 4.5 percent of the agricultural GMP and the Kenyan GMP respectively (Mold, 2017). The dairy sector generates an estimated 1 million, 0.5 million, and 0.5 million jobs at the farm level, direct wage employment, and in support services respectively. Hence the dairy sector is important in poverty eradication (USAID, 2016). Kenya exports substantial milk products which include milk powder, long-life milk, and ghee estimated at 10.9 million kilograms per annum (KDB, 2019).

There are more than 1.8 million smallholder milk-producing households that own one to three cows in the country (IFAD and UNEP, 2013). The dairy cattle population in Kenya is estimated at 4.3 million, of whom eighty percent is owned by smallholder farmers (Peeler *et al*., 2018). The country produces on average 5.1 billion litres of milk per annum against a milk demand of 5.2 billion litres. This leaves the country with a deficit of 100 million litres of milk every year. This high demand is attributable to a rising middle class, increasing urbanization, and export opportunities within East Africa (KDB, 2019). The milk processing capacity in the Kenya still remains low at 648 million litres annually (KDB, 2019). However, processors still do not operate optimally due to competition from the informal sector and seasonality of the produce (FAO, 2017). The milk production levels still remain low due to the challenge of climate change which negatively

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affects fodder production, because the majority of farmers rely on rain for fodder production (KDB, 2019).

The dairy cow population in Makueni County is estimated at 22,353 with estimated total milk production of approximately 26 million litres against a demand of 340 million litres and a processing capacity of 0.47 million litres per annum. The dairy sector in Makueni County employs about 21-40 percent of the entire population in the county with production being dominated by smallholder farmers who account for 80 percent of the total milk produced (MoALF, 2019). On average each dairy farmer owns between one to four animals (MoALF, 2019). The revitalization of the Makueni County dairy sector started with the artificial insemination program funded by the county government in the year 2014. The objective was to produce breeds that are adaptable to the local climatic conditions and genetically high-yielding. The second initiative entailed rolling out a project characterized by massive fodder farming promotion. All these initiatives, strategically geared toward expanding milk productivity in the county of Makueni, were complimented by enhancing the operational capacity of the Kikima milk processing plant which entailed increasing its processing capacity to provide a ready market to the smallholder farmers (Makueni County CIDP, 2013 - 2017).

The Kikima milk processing plant is located in Makueni County, within Mbooni sub-county. The dairy plant was established by the members of Kikima Dairy Cooperative Society in the year 1971 targeting smallholder dairy farmers within Makueni County and has been operational for the last 51 years. The milk processing plant later received support in form of a grant to acquire additional equipment to increase its processing capacity from the area county government in the year 2014. The dairy plant is owned by 951 members of Kikima Dairy Cooperative Society. The processing capacity of the plant is estimated at 300 litres per hour and 6,600 litres of milk per day (Kikima Dairy Plant Annual Review Report, 2020). The plant so far has acquired an additional storage tank, pasteurizer machine, and packaging equipment which have improved its value addition capability. The plant produces three products; mala milk, fresh milk, and pasteurized branded milk dubbed ‘Makueni Fresh’. So far, the plant has secured a ready market for its products with nearby supermarkets and schools (Kikima Dairy Plant Annual Review Report, 2020). However, milk production in Makueni County faces the challenge of seasonal fluctuation of production and poor infrastructure whereby the milk-producing areas tend to have poor road networks as well as informal milk trade (MoALF, 2019).

Since its inception in 1971, Kikima milk processing plant has had remarkable progress. For example, setting up a cold room, acquiring additional standard cooling equipment, procuring an additional pasteurizer machine, and packaging equipment. Hence having an improved value addition capacity (Kikima Dairy Plant Annual Review Report, 2020). However, its effect on the welfare of farmers is not well known. There is lack of empirical studies that have evaluated the impact of Kikima milk processing plant on smallholder farmers’ welfare. Thus, it is not clear whether the milk processing plant has made any noticeable welfare and livelihood changes in terms of farm income and contribution to the economic empowerment of the dairy farmers. There has been extensive research on the impact of developmental projects on farmers’ welfare in Kenya and other parts of the world. For instance; Mwambi *et al.,* (2016), Mmbando (2014), Manda *et al.,* (2021) and Tuan (2012). However, there is scanty knowledge regarding the impact of agro-processing developmental projects initiated by the devolved system of governments in Kenya. Therefore, the current study fills this gap in knowledge by studying the impact of participation in milk processing on smallholder farmers’ welfare, using the case of Kikima Dairy Cooperative Society milk processing plant in Makueni County.

1.2 Study area

The study was conducted in Makueni County. The county was selected purposively because it hosts the milk processing plant of interest in this study. The County is characterized by two rainy seasons, whereby the short rains occur in November-December while the long rains occur in March-April. The hilly parts of Mbooni sub-county where the Kikima milk processing plant is located receive approximately 800 - 1200mm of rainfall per annum. This level of rainfall makes the sub-county suitable for horticulture, fodder production and dairy farming. Thirty-five percent of the households in Mbooni sub-county produce and sell milk (MoALF, 2019). Data were collected from dairy farmers in Mbooni and Kilome sub-counties of Makueni County as shown in Figure 1.

Kikima dairy cooperative society plant is located at Kikima shopping center in Mbooni Sub-county of Makueni County. Majority of the smallholder farmers who deliver their milk to this plant are from within Mbooni sub-county, with very few farmers from the neighboring regions of Kaiti sub-county, Makueni sub-county, Mwala and Machakos delivering their milk to the plant (Kikima Dairy Plant Annual Review Report, 2020). The control group respondents were drawn from the neighboring Sub-county of Kilome. Kilome and Mbooni Sub-counties are separated geographically by two other sub-counties namely; Kaiti and Makueni sub-counties.

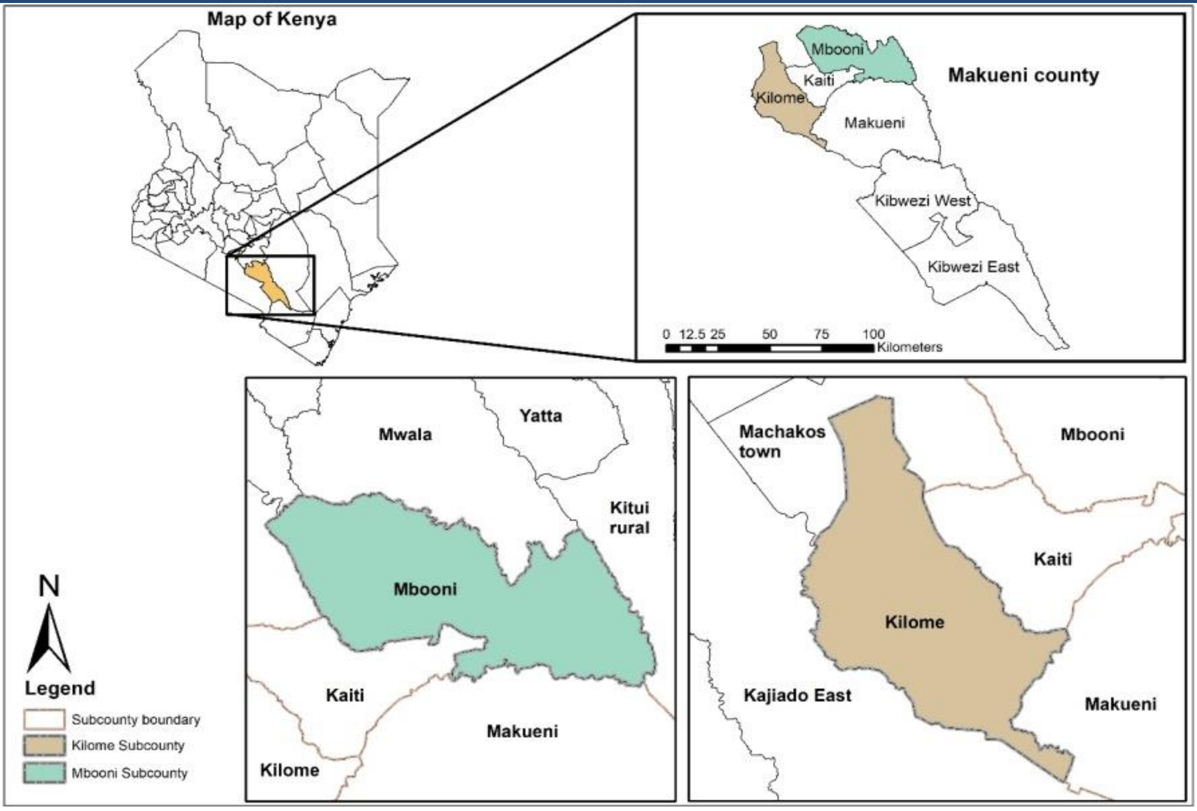

Figure 1: Map of the study sites (Mbooni and Kilome sub-counties) in Makueni county
Source: Created from Arc-GIS by Author

2.1 Conceptual framework

Farmers' decision to participate in milk processing was hypothesized to be influenced by the farmers' socio-economic, farm, and institutional characteristics like education level, age, primary occupation, sex, household size, experience, farm size, distance to the main road, price of milk per litre, access to extension services, credit access and group membership. The respective farmers' socio-economic, farm and institutional characteristics also condition the impact on welfare as shown on Figure 2.

The milk processing plant is expected to provide farmers with a ready market. Similarly, since the processing of milk has the potential to enhance shelf life and retail price of milk (FAO, 2017), this is expected to have a positive effect on the welfare of the dairy farmers in terms of farm income, improved household income, improved food and nutrition security, poverty reduction as well as improved natural resource base. Although, all the above listed welfare indicators are important, the current study focused on farm income as the only welfare indicator as data on household income, food security, poverty status, and natural resource base were not collected or available from secondary sources. In this study, gross profit from the sale of milk was used as a proxy for farm income.

2.2 Theoretical framework

This study was anchored on random utility theory which was developed by Thurstone (1927). According to this framework, the farmer's objective is to maximize utility. A household is assumed to maximize a welfare-enhancing factor which is the utility. Therefore, a farmer's decision to participate or not to participate is grounded on the utility they are likely to derive, with an assumption that farmers are risk-neutral. An individual is assumed to maximize his/her utility from a given project if the utility derived from participating in that project is greater than the utility derived from participating in an alternative project.

The utility that an individual derives from participating in a given project is presumed to be influenced by the project's attributes and the attributes of the individual (Maddala *et al.*, 2001). However, these attributes might be perceived differently by different agents, whose socio-economic characteristics will as well affect or influence utility. As a result, an individual may perhaps not select what appears to the analyst as the ideal alternative. To explain such deviations in project choice, an arbitrary element, ε, is incorporated as a part of the participants' group utility function (McFadden, 1978).

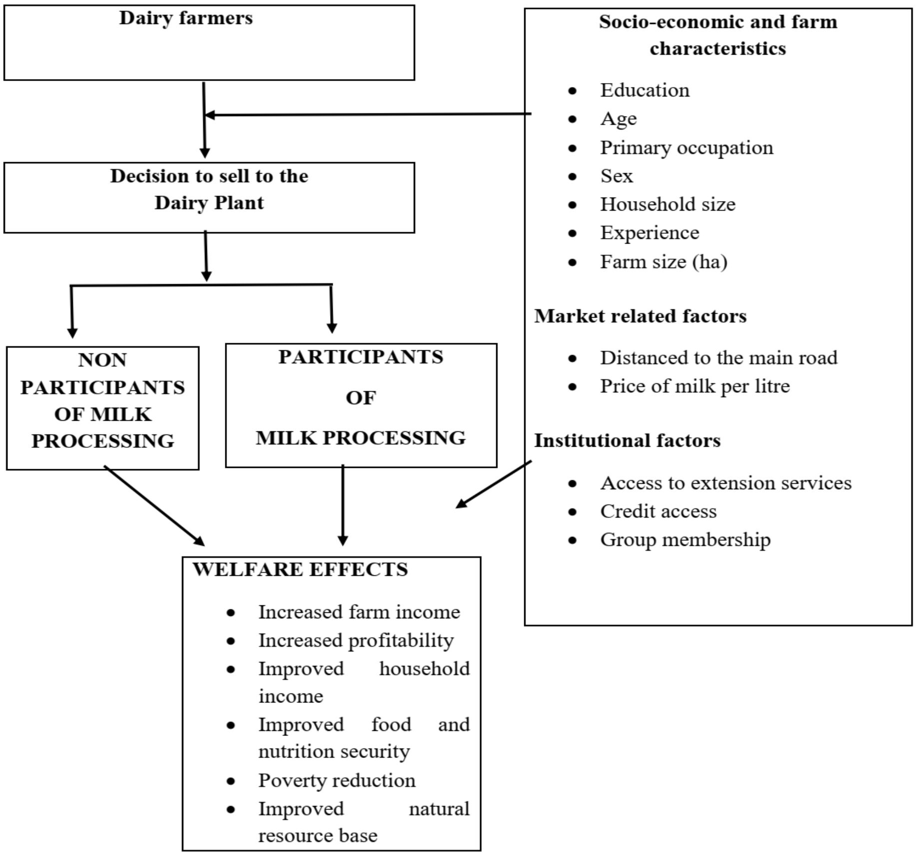

Figure 2: Illustration of farmers' motivation to participate in milk processing and implications on welfare
Source: Author's conceptualization

Dairy farmers were therefore, assumed to settle for the milk buyer(s) providing them with maximum utility (Abdulai and Huffman, 2014). Under the assumptions that the utility (farm income) farmers derive from milk processing (MP) participation is Y_jMP, and the utility from non-participation is represented as Y_jNMP.

The two groups can be specified as:
$YjMP = X_j\beta MP + U_jMP$………….........……..... (1)
$Y_jNMP = X_j\beta NMP + U_jNMP$……………………….. (2)

Where X_j is a vector of independent factors of the household, institutional and farm characteristics; βMP and βNMP respectively represent the parameter estimates for MP and NMP; U_jMP and U_jNMP are the error terms, which are Independent and Identically Distributed (IID). Therefore, a rational farmer will participate in milk processing if he or she gets maximum utility from participation and vice versa. This can be expressed as $Y_jMP > Y_jNMP$ (Pitt, 1983).

From the empirical data, some farmer attributes are observable. However, other attributes such as the perceived net benefit(s) of participating in milk processing are not known or revealed to the researcher. In this scenario, the perceived benefits derived from participating in milk processing can be represented by a latent variable D_J^*, which can be expressed in a latent variable model as a function of the observed attributes and characteristics, denoted as Z, as follows:
$D_j^* = Z_J\gamma + \varepsilon_J$; $D_j^* = 1$ if $D_J > 0$; $D_J^* = 0$ if $D_J \leq 0$ ………………………… (3)

D_J is a dummy variable that equals one for farmers who participated in milk processing and zero for non-participants. While γ is the parameter being estimated. A rational farmer who is utility-maximizing is expected to participate in milk processing if the perceived net benefits of participation are more than those of not participating. The error term ε, captures any measurement errors and the factors which were known to the respondent but unobserved by the researcher. Z represents the factors influencing participation (Pitt, 1983).

3.1 METHODOLOGY AND DATA ANALYSIS

The endogenous switching regression (ESR) model was used to evaluate the impact of farmers' participation in milk processing on farm income. The estimation using this method proceeds in two stages. A probit regression is used in the first stage to determine the probability of participation in milk processing. Since the farmers decide to participate or not to participate in milk processing, the observed net benefits take the following values:
Group 0 (NMP): $Y_{JNMP} = X_J\, \beta_{NMP} + U_{JNMP}$ if $D_J = 0$ …………….…………. (4)

Group 1 (MP): $Y_{JMP} = X_J\ \beta_{MP} + U_{JMP}$ if $D_J = 1$ ……………………..………..…. (5)

Where Y_{JMP} and Y_{JNMP} are the outcome variables (farm income) for milk processing (MP) and non-milk processing (NMP) groups respectively, X_J is a vector of independent variables of household characteristics, farm, and institutional factors. The vector β in Equation (4) and Equation (5) represents the parameters that are being estimated. If self-selection occurs in milk processing (MP) participation decision, it may lead to non-zero covariance between the error terms of the outcome equation and MP participation decision equation. The error terms U_{JMP}, and U_{JNMP} are assumed to have a trivariate normal distribution with zero mean and covariance matrix as represented in Equation (6):

$$\text{Cov}\ (U_A \text{ and } U_N) = \sum = \begin{pmatrix} \sigma^2{}_A & \sigma_{AN} & \sigma_{A\varepsilon} \\ \sigma_{AN} & \sigma^2{}_N & \sigma_{N\varepsilon} \\ \sigma_{A\varepsilon} & \sigma_{N\varepsilon} & \sigma^2{}_\varepsilon \end{pmatrix} \ldots\ldots..\ (6)$$

Where; *A = MP; N = NMP*
Var (U_A) = $\sigma^2{}_A$; Var (U_N) = $\sigma^2{}_N$; Var (ε) = $\sigma^2{}_\varepsilon$
Cov (U_A, U_N) = σ_{AN}; cov (U_A, ε) = $\sigma_{A\varepsilon}$; cov ($U_{N,}$ ε) = $\sigma_{N\varepsilon}$

For this reason, the error terms in Equation (6), conditional on the sample selection criterion, have non-zero expected values, and ordinary least squares estimates of coefficients β_{MP} and β_{NMP} also suffer from sample selection bias (Lee, 1982). The values of the truncated error term (U_{MP} |D = 1) and (U_{NMP} |D = 0) are then given as;

$$(U_{NMP}\ |D = 0) = E\ (U_{NMP}\ |\varepsilon \leq -Z'Y) = \sigma_{NMP\varepsilon}\ \frac{\partial\left(\frac{Z'Y}{\sigma}\right)}{1-\theta\left(\frac{Z'Y}{\sigma}\right)} = \sigma_{NMP\varepsilon}\lambda_{NMP} \ldots\ldots\ldots\ldots\ldots(7)$$

$$\text{and } (U_{MP}\ |D = 1) = E\ (U_{MP}\ |\varepsilon - Z'Y) = \sigma_{MP\varepsilon}\ \frac{\partial\left(\frac{Z'Y}{\sigma}\right)}{1-\theta\left(\frac{Z'Y}{\sigma}\right)} = \sigma_{MP\varepsilon}\lambda_{MP} \ldots\ldots\ldots\ldots\ldots\ (8)$$

Where ∂ and θ are the probability density and cumulative distribution function of the standard normal distribution respectively. The ratio of ∂ and θ evaluated at $Z'Y$ represent the inverse Mills ratio λ_{MP} , λ_{NMP} which are also known as the selectivity terms (incorporated into Equations [7] and [8]) and they are useful in accounting for selection bias. Where λ_{MP} and λ_{NMP} respectively represents the inverse mills ratios for participants and nor-participants, while σ represents the covariance of the error terms. When the error term of the selection equation is correlated with the error terms of the outcome equation for the participants and non-participants, then we have a selection bias problem. Thus, estimates from the selection equation are used to compute λ_{MP} and λ_{NMP}, which are then added to the outcome equations to correct for selection bias. If $\sigma_{NMP\varepsilon}$ and $\sigma_{MP\varepsilon}$ in Equations (7) and (8) are statistically significant, endogenous switching exists.

The estimates (Y) from Equation (4) are then used in calculating the selectivity terms ($\lambda_{MP}, \lambda_{NMP}$) according to Equations (7) and (8). This two-step approach has a limitation in that it generates heteroscedastic residuals and hence requires complex adjustments to generate consistent standard errors. To overcome this challenge, this study applied the full information maximum likelihood method (Lokshin and Sajaia, 2004). Of keen interest are the signs and significance levels of the correlation coefficients from the estimates. In this study, both the treatment and heterogeneity effects on income were assessed. This is because the impact of participation in MP on farm income was of interest in this study. The Full Information Maximum Likelihood (FIML) estimation method which simultaneously estimates the probit criterion or selection equation and the outcome equations to yield consistent standard errors was used in estimating the ESR model owing to its efficiency in estimation (Lee and Trost, 1978; Lokshin and Sajaia, 2004).

Although the FIML ESR model is identified through non-linearities of λ_{MP} and λ_{NMP}, (Lokshin and Sajaia 2004), a better identification of the ESR model requires an exclusion restriction. That is, for the ESR model to be correctly specified, the selection equation should contain at least one selection instrument in addition to those generated by the non-linearity of the selection model correlated with milk processing participation but uncorrelated directly with farm income realized from milk proceeds. The selection instrument used in the current study is age of the household head. The validity of the instrument was tested using falsification test. The results showed that the selected instrument could be considered as valid as it was statistically significant in explaining participation decision *[χ2 = 6.94 (p-value = 0.020*)] but is not statistically significant in explaining the farm income function *[F = 2.11 (p-value= 0.343)]* and *[F = 1.14 (p = 0.441)]* for participants and non-participants, respectively, verifying the validity of the instrument. Therefore, age was not directly correlated with farm income, except through participation in the milk processing project. The variable Age was also statistically significant in most equations pertaining the decision to participate in milk processing (Table 2) but not of the income (outcome) equations (Table 2).

3.2 Endogenous Switching Regression (ESR) method

ESR method was developed by Lee (1997). This method treats selectivity as an omitted variable problem thus accounting for selection bias (Heckman, 1979). As compared to the Heckman model, in using ESR farm outcomes like gross margins and income can be observed for all participants and non-participants in the sample. Therefore, in the ESR approach, in order to capture the differential responses of the participant and non-participant groups, respondents are partitioned to create a clear control and treatment group (Heckman, 1979). Given the interest of this study in assessing the impact of participating in milk processing (MP), this study employed the ESR model combined with an instrumental variable for identifying the selection equation to account for selectivity bias.

When households are not randomly exposed to a treatment, they either self-select for treatment or the technologies (treatment) are directed to the targeted households (Alene *et al.,* 2008). Hence, participation in milk processing is potentially endogenous. Failure to account for this selection bias as well as endogeneity could potentially obscure the true impact of the dairy plant. The endogenous switching regression method addresses the selection and endogeneity problems by estimating a simultaneous equations model with endogenous switching using full information maximum likelihood (Lokshin and Sajaia, 2004). Thus, through modeling both selection and outcome equations, ESR accounts for selection bias arising from unobserved characteristics, controls for structural differences between participants and the non-participants regarding the outcome functions (Alene *et al.,* 2008). Propensity Score Matching method was unsuitable for the current study due to its shortcoming of inability to account for unobservable factors, resulting in biased estimates (it presents the problem of sample selection bias or auto-selection bias) (Caliendo and Kopeining, 2008).

3.3 Estimating heterogeneity and treatment effects on income

The ESR model can be used to compare the expected income of farmers who chose to participate in MP as illustrated in Equation (8) and those that chose not to participate as illustrated in Equation (9). In the hypothetical counterfactual case, given that the households that participated in milk processing did not participate, the expected income is as illustrated in Equation (10). Equation (11) illustrates the hypothetical counterfactual case of the expected income given that the households that did not participate in milk processing participated. The conditional expectations for the outcome variables in the above four mentioned cases are as illustrated in Table 1. Where Equations (9) and (10) illustrate observed expected farm income while Equations (11) and (12) represent counterfactual expected farm income.

D_i = 1 if households participated in MP
D_i = 0 if households did not participate in MP
Y_{JMP} = Income level if the households participated in MP
Y_{JNMP} = Income level if the households did not participate in MP
TT = Treatment effect of milk processing on the treated (i.e.: households that participated)
TU = Treatment effect of milk processing on the untreated (i.e.: households that did not participate)
BH = represents the base heterogeneity effect of households that participated (BH_{MP}), and did not participate (BH_{NMP});
TH = TT-TU represents the transitional heterogeneity.

$E(Y_{JMP} | D = 1) = X\beta_{JMP} + \sigma_{MP\varepsilon}\lambda_{MP}$ …………...... (9)
$E(Y_{JNMP} | D = 0) = X\beta_{JNMP} + \sigma_{NMP\varepsilon}\lambda_{NMP}$ ……….... (10)
$E(Y_{JNMP} | D = 1) = X\beta_{JMP} + \sigma_{NMP\varepsilon}\lambda_{MP}$ ….……..… (11)
$E(Y_{JMP} | D = 0) = X\beta_{JNMP} + \sigma_{MP\varepsilon}\lambda_{NMP}$ …………... (12)

Equations [9, 10] illustrate the actual expectations which were to be observed in the sample. While Equations [11, 12] illustrate the counterfactual expected outcomes. The effect of the treatment on the treated (TT) was given by the difference between Equations (9) and (11) (Heckman and Vytlacil, 2001).

$TT = E(Y_{JMP} | D = 1) - (Y_{JNMP} | D = 1) = X(\beta_{JMP} - \beta_{JMP}) + (\sigma_{MP\varepsilon} - \sigma_{NMP\varepsilon})\lambda_{MP}$ …….. (13)

The above equation denotes the effect of participation in milk processing on the income of farmers who actually participated.

Table 1: Heterogeneity and treatment effects

Sub-samples	Decision stage		Treatment effects
	To participate	Not to participate	
Farm households that participated in MP	(9) $E(Y_{JMP} \| D = 1)$	(11) $E(Y_{JNMP} \| D = 1)$	TT
Farm households that did not participate	(12) $E(Y_{JMP} \| D = 0)$	(10) $E(Y_{JNMP} \| D = 0)$	TU
Heterogeneity effects	BH_{MP}	BH_{NMP}	TH

While the impact of the treatment on the untreated (TU) for farmers that actually did not participate in MP was calculated as the difference between Equation (12) and (10).

$TU = E(Y_{JMP} | D = 0) - (Y_{JNMP} | D = 0) = X(\beta_{JMP} - \beta_{JMP}) + (\sigma_{MP\varepsilon} - \sigma_{NMP\varepsilon})\lambda_{NMP}$ …...…….. (14)

The heterogeneity effects for the treated group were obtained as the difference between Equations (9) and (12). The heterogeneity effects entail the differences in the outcome due to the inherent attributes of the respondents such as innate ability and not that of the treatment (Carter and Milon, 2005);

$BH_{CF} = E(Y_{JMP} | D = 1) - (Y_{JMP} | D = 0) = \beta_{JMP}(X_{JMP} - X_{NJMP}) + (\lambda_{MP} - \lambda_{NMP})\sigma_{MP\varepsilon}$ ………(15)

While heterogeneity effects for the group that did not participate in milk processing (NMP) was given as the difference between Equation (11) and Equation (10)

BH_{NCF} = E (Y_{JNMP} |D = 1) - (Y_{JNMP} |D = 0) = β_{JNMP} (X_{JMP} - X_{NJMP}) + $(\lambda_{MP} - \lambda_{NMP})\sigma_{MP\varepsilon}$ ………. (16)

Transitional heterogeneity was given as the difference between Equations (13) and (14) ((TT) and (TU)). Transitional heterogeneity establishes whether the effect of participating in milk processing is smaller or larger for households that participated or for those households that actually did not participate in the counterfactual case that they chose to participate.

3.4 Sample size determination

The samples size for this study was determined using the Cochran (1963) formula. This formula is specified as:

$$n = \frac{Z^2pq}{e^2} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (17)$$

Where *n* is the sample size being determined, *Z* is the critical value of the standard normal distribution for the desired confidence level taken as 95 percent, which is 1.96, *P* is the proportion of the target population of interest (the population of participants), which is 0.13 according to the Makueni County climate risk profiling report (MoALF, 2019). This represents the proportion of dairy farmers in Makueni County that sell their milk to Kikima dairy cooperative society plant. While q is 1– p. *e* is the allowable margin or desired level of precision set at 5%. According to Barlett *et al.,* (2001), generally the acceptable margin of error or desired level of precision for educational and social researches is 5% or 0.05. Therefore;

$$n = \frac{(1.96)^2(0.13)(1-0.13)}{0.05^2} = 174 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (18)$$

To cater for non-response and incomplete questionnaires, data were collected from 200 respondents, consisting of 100 participants and 100 non-participants.

3.5 Sampling procedure, data types, collection methods and analysis

Data were collected from a survey of dairy farmers in Mbooni and Kilome sub-counties of Makueni County. This study adopted a multistage sampling technique to obtain its respondents. In the first stage, Makueni County was purposively selected. This is due to the fact that the dairy plant is located in Makueni County serving the dairy farmers in this county. The county has six sub-counties namely; Kibwezi East, Kibwezi West, Kilome, Kaiti, Makueni and Mbooni. A good portion of smallholder farmers from Mbooni, Makueni and Kaiti sub-counties were selling their milk to the dairy plant (Kikima Dairy Plant Annual Review Report, 2020).

In the second stage, Mbooni and Kilome sub-counties were purposively selected as the regions from which the treated and control group respondents were to be drawn from respectively. Mbooni sub-county was preferred to the other two sub-counties (Makueni and Kaiti) because after examining the database of farmers selling milk to Kikima dairy plant, it was discovered that, there were critical inconsistencies in delivering milk to the plant by farmers from Makueni and Kaiti sub-counties. Therefore, it was preferred to have the treated group respondents drawn from Mbooni sub-county. While Kilome sub-county was preferred as the region from which to draw the control group respondents because it has been found to have favourable weather conditions for fodder production, similar to the weather conditions in Mbooni sub-county where the dairy plant operates. Twenty-eight percent of the households in Kilome sub-county have also been found to practice dairy farming (MoALF, 2019).

In the third stage, respondents were stratified by participation to form two strata: one comprising of participants and the other comprising non-participants. Whereby, a list of all farmers who have been selling their milk to the dairy plant consistently for the last three years was obtained from the plants' database. This list formed the sampling frame for the project participants, which consisted of 350 farmers. While for the non-participants, a list of registered dairy farmer groups and their members, within Kilome sub-county was obtained from the county governments' department of cooperatives. To ensure the treated group was comparable with the control group, only farmers who had been practicing commercial dairy farming for more than three years were considered fit for the control group. This list formed the sampling frame for the project non-participants, which consisted of 250 farmers. In the fourth stage, respondents were randomly selected from each sampling frame using random numbers which were generated using Microsoft Excel, to generate a sub-sample of 100 participants and 100 non-participants who constituted the actual number of respondents who were interviewed eventually. This study used primary cross-sectional data collected through personal interviews using a pre-tested, semi-structured questionnaire. These data were analyzed using STATA Version 14 after undergoing cleaning to ensure there were no outliers.

4.1 RESULTS AND DISCUSSION

Table 2 shows results from the endogenous switching regression model which was estimated using the full information maximum likelihood estimation (FIML) method. All the coefficients presented in Table 2 are interpreted as normal probit coefficients. From the results presented in Table 2, the Wald test was found to be highly significant, indicating the goodness of fit of the endogenous switching regression model for analysis. This means there was an endogeneity problem that was controlled for, hence justifying the use of endogenous switching regression model in the analysis. The Wald test of independence of the selection equation and outcome equation was significant at 1 percent. This means that the null hypothesis of no correlation between participation in milk processing and farm income is rejected. This means that the independent variables in the outcome equation together explain the variation in income, which is the outcome variable.

The results presented in Table 2 indicate that the likelihood ratio test for joint independence of the three equations was statistically significant. This implies that the three equations are dependent of each other. The covariance terms rho_1 and rho_2 as shown in Table 2 are both negative but are significant only for the correlation between the participation choice equation and the milk processing participants' income equation. Since rho_1 is negative and significantly different from zero, this implies that there was self-selection in milk processing participation decision. This means that participation in milk processing may not have had the same effect on the non-participants if they chose to participate in milk processing (Abdulai and Huffman, 2014). The negative sign implies the presence of a positive bias, giving an indication that farmers with above average milk income had a higher probability of participating in milk processing. This is similar and consistent with the findings by (Barrett and Croft, 2012). Price of milk as an independent variable was left out in modelling the participation equation since the price of milk offered by the dairy plant was constant at Kshs 32, hence no variation.

Table 2: Endogenous switching regression model results for farm income

Variables	***Selection equation (Pooled sample)***		***Participants n = 100***		***(Non-Participants) n = 100***	
	Coef.	***z- value***	***Coef.***	***z- value***	***Coef.***	***z- value***
Sex of the HH head (1= Male, 0=Female)	-0.65	0.26	2757.49	0.26	4312.61	0.22
HH head education (Years of schooling)	-0.01	0.58	5269.19**	2.24	6228.33	1.30
HH head primary occupation (1=Farmer,0=otherwise)	0.54***	2.64	9842.45	0.51	12308.10	0.48
HH head experience (Years of dairy farming)	0.05*	1.70	-1156.94	1.00	-3649.04*	1.94
Household size	-0.09	1.47	-5429.21	-1.45	3962.04	0.77
Farm size (Hectares)	0.12	1.27	0.18	1.08	17022.52	1.24
Access to credit services (1= Yes, 0= No)	-0.06	0.17	51130.72***	3.15	15336.51	0.72
Distance from the farm to the road (Km)	0.19	1..49	382.73	0.03	11999.40	0.66
Access to extension services	0.03	0.12	5701.28**	2.01	15627.83***	3.02
Membership to a farmer group (1= Yes, 0= No)	0.40	0.99	-4397.23	0.13	-1775.37	0.05
HH head Age (Years)	0.06	2.64				
Breeding method used (1= AI, 0= Otherwise)			-4628.63	0.13	-2488.07	0.06
Cost of fodder (Kshs)			-8.77*	1.72	1.74	0.40
Cost of veterinary services (Kshs)			4.90	0.56	1.88	0.18
Cost of mineral supplements (Kshs)			-3.05	1.38	8.95***	2.16
Cost of labour (Kshs)			-0.99	0.53	2.73	1.44
Constant	-0.64	0.887	149194.3	6.23	147636.41	2.93
/lns1	11.57	1516.34				
/lns2	11.15	222.76				
Sigma_1	104779.51					
Sigma_2	69637.07					
rho_1	-0.83***					
rho_2	-0.10					
Loglikelihood	-2650.57					
Wald test χ^2 (17)	45.54***					
χ 2 statistics for overidentification				0.72 [0.43]		
LR test of independence equations χ^2 (1) 13.71 ***						

, **, ** denote significance at 10 percent, 5 percent and 1 percent respectively

Note: p value in square brackets, denote residuals from the first-stage regressions for age

Source: Survey Data (2022).

The covariance term for the non-participants (rho_2) was statistically insignificant. This implies that in the absence of milk processing, there would be no significant difference in the average annual milk income realized by the project participants and non-participants caused by unobserved factors (Lokshin and Sajaia, 2004). The identification of the model requires that at least one variable in the selection equation would not appear in the outcome equation. In this study age of the household head was used as the identifying instrument. Age was expected to influence participation decision but not directly affect milk income. The age residual estimates were not statistically significant, this implied that the coefficients of the age variable had been consistently estimated (Wooldridge 2015).

To further check for the presence of multicollinearity among the independent variables in the endogenous switching regression model, the Variance Inflation Factor (VIF) was estimated. The rule is, if the VIF is greater than 5, that is an indication of multicollinearity among the exogenous variables (Green, 2003). The VIF test values ranged between 1.09 - 1.50 with the mean VIF being 1.29. This was an indication that there was no evidence of multicollinearity. To further rule out the presence of multicollinearity among the independent variables in the endogenous switching regression model, a partial correlation test was carried out. The results of the partial correlation test for multicollinearity revealed the absence of serious correlation as the correlation magnitude for all variables was found to be below 0.5.

To test for heteroscedasticity, the Breusch-Pagan/Cook-Weisberg test was applied with the null hypothesis being that there was no heteroscedasticity (constant variance) among the error terms. The Chi-square was 0.40 with one degree of freedom and was found to be insignificant at a *p*-value of 0.53. This implied that there was no heteroscedasticity. Thus, the null hypothesis of constant error variance was not rejected. The results indicate that the positive and significant factors influencing the level of annual income among the project participants are level of education of the household head, credit access and access to extension services. For the non-participants, access to extension services and the cost of mineral supplements had a positive and significant effect on the level of income realized by the farmers.

The positive relationship between education level for participants and the level of farm income could be due to the fact that farmers with a higher level of education can comprehend and apply efficient methods of production hence maximizing on their profitability (Olayiwola, 2019). The positive relationship between age and farm income is likely due to the fact that older farmers were more experienced in dairy farming and were well aware of the efficient and relevant dairy enterprise management practices as well as having gathered information on profitable marketing channels over their years of dairy farming. This is similar to the findings by (Olayiwola, 2019), where the age of the household head was found to positively influence the gross margin levels realized by farmers.

The positive relationship between access to extension services and the farm income level for both participants and non-participants could be attributed to the fact that improved access to extension services was likely to improve on farmer's knowledge on management practices such as pasture management, feeding methods, parasite and disease management, breeding methods as well as hay making, which were likely to improve on the overall productivity per cow, which in turn would increase the gross margin realized. These results agree with the findings of Abdulai and Huffman (2014) who noted that access to extension services had a positive relationship with the productivity and farm income of rice farmers.

The positive relationship between the cost of mineral supplements and milk income may be attributed to the fact that mineral supplements play role in milk secretion, lowers the incidence of diseases and reproductive health problems hence farmers incur lesser input costs in managing diseases (Bidzakin *et al.*, 2019). Therefore, it is likely that the participants had optimally utilized mineral supplements. The positive relationship between credit access for the participants and level of income is in line with the expectation that access to credit enhances the ability of a farmer to procure necessary inputs such as mineral supplements, fodder, AI services and other veterinary services, pay for labour as well as being able to procure exotic breeds of cows, and this would increase the milk yield realized and subsequently increase the gross margin level. This is similar to the findings by Bidzakin *et al.,* (2019) who reported an improvement in yield by farmers who had accessed credit.

The negative and significant determinant of milk income among the participants was the cost of fodder only. While for the non-participants, only the level of experience in dairy farming had a negative and significant influence on the level of annual milk income realized by the farmers. The negative relationship between the cost of fodder and income level implies that as the cost of fodder increases, the level of milk income realized by a farmer is likely to decrease. This is in line with the theory that costs have an inverse relationship with gross margin. This is because, the cost of fodder is expected to increase total variable cost which is subtracted from the total revenue to give the gross margin (Samboko, 2011).

The inverse relationship between experience and level of income is in contrast to the expectation that a farmer having practiced dairy farming for a longer period of time, he/she would have gained hands-on knowledge and skills pertaining the efficient management practices. For instance, pasture management, pest and disease management and breeding methods. However, the observed negative relationship may be attributed to possible inefficiencies in production and mostly due to lack of training on best management practices, particularly for the dairy enterprise. This result is contrary to the findings by

Samboko (2011) and Wainaina (2014) who reported a positive relationship between farmers' farm experience and productivity levels.

As shown in Table 3, the results indicate that there is a significant and negative correlation between participating in milk processing and the level of milk income realized, implying that participation reduces farmers' income and also had the potential to reduce the income realized by the non-participants if they had participated. The causal effect of milk processing for the treated group (participants) was about Kshs 60,329.38. This represents about 49.8 percent decrease in the income realized by the farmers who participated in milk processing. This is because participating lowers the income of participants from Kshs 121,124.80 to Kshs 60,795.42. The causal effect for the non-participants (control group), if they had chosen to participate in milk processing was found to be Kshs 59,954.20.

4.2 Impact estimates

The ATT and ATU are presented in Table 3.

Table 3: Impact of participation in milk processing on farmers' income

Outcome variable	Adoption status	Predictions		Treatment Effect	T-Value
		Treated	Control		
Annual Milk Income per Cow	ATT	60 795.42	121 124.80	-60 329.38***	-8.19
	ATU	135 155.60	195 109.80	-59 954.20***	-10.87
	Heterogeneity Effect	-74 360.18	-73 985.00		

*, **, *** denote significance at 10 percent, 5 percent and 1 percent respectively

Source: Survey Data (2022).

This represents about 30.7 percent decrease in the income that the non-participants would have realized. This is because participating would lower the income realized by non-participants from Kshs 195,109.80 to Kshs 135,155.60. The reported negative impact in this study is also consistent with that of Mwambi *et al.,* (2016), who reported that participation in new agribusiness projects was not sufficient to improve farm income of Avocado fruit farmers. This negative impact was attributed to inefficient implementation of farming arrangements to promote spillover effects on other household enterprises. This study, therefore, contributes to literature by showing that the impact of agro-processing as well as agribusiness projects is not always positive and can go either way, thus the impact can be positive or negative.

This finding is in contrast with the view that participation in agro-processing projects has the potential to significantly improve farm income and profits realized by smallholder farmers (Cai *et al.,* 2008; Feng *et al.,* 2020; Tuan, 2012). The above finding is also in contrast with that of to that of Manda *et al.,* (2021), who found out that smallholder farmers' participation in both single and multiple–commodity markets was positively and significantly associated with income. This was attributed to the favourable and enabling policy environment created by the local government. This negative impact on farmers' income as reported in this study is also in contrast with that of to that Mmbando (2014), who established market channel choice has positive impact on household welfare. Therefore, participation in wholesale market channels was found to have significant positive impact on welfare.

5.1 CONCLUSIONS

The hypothesis of the current study that participation in milk processing has no impact on farm income was rejected. Therefore, this study concludes that participation in milk processing has a negative impact on the farm income realized by smallholder farmers. Thus, this study further concludes that participating in milk processing is not a guarantee for realizing increased or higher farm income among farmers in Mbooni and Kilome sub-counties. This could be attributed to the relatively lower price offered per litre of milk by the dairy plant which has a direct effect on the farmers' gross margin, as well as the higher production costs realized by participants which are likely to be as a result of the higher costs incurred in the purchase of fodder compared to the non-participants.

This study further concludes that smallholder farmers in Mbooni and Kilome sub-counties of Makueni County choose to participate in milk processing because of other motives, gains or factors and not necessarily financial gains. This is because the participants of milk processing sold their milk to the plant at a lower price despite having access to other channels offering better prices. This is attributable to the participants being risk-averse and therefore they preferred selling to the dairy plant where they were guaranteed of being paid as opposed to selling to middlemen in the informal sector who might default on payment. The participants were also risk-averse in that they avoided selling to the informal market where demand is not guaranteed as demand in the informal sector keeps on fluctuating. For instance, when schools close, farmers who normally sell their milk to schools have to look for another market.

5.2 POLICY RECOMMENDATIONS

Based on the finding that the milk price offered at the plant was a key determinant of profits realized by farmers, this study recommends that the plant management should consider offering a quality-based payments to farmers. This would potentially solve the problem of participants of milk processing getting low prices for their milk. This will boost farm income and eventually the welfare of the participants would improve, as well as attract participation by other farmers. Notably, being paid on a flat rate per litre of milk leaves the processor to benefit more than the farmers from the by-products of milk.

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