Journal of Agricultural Economics and Development Vol. 4(6), pp. 095-104, September 2015
Available online at http://academeresearchjournals.org/journal/jaed
ISSN 2327-3151 ©2015 Academe Research Journals

Full Length Research Paper

Determinants of smallholder dairy farming adoption in Malawi: A microeconometric analysis

W. G. Lipita[1]*, D. H. Ng'ong'ola[2], L. A. Kamwanja, C. Mataya, T. N. Gondwe[2] and H. Kankwamba[2]

[1]Department of Animal Health and Livestock Development, Lilongwe, Malawi.
[2]Bunda College of Agriculture, Lilongwe, Malawi.

Accepted 7 September, 2015

Understanding determinants of smallholder dairy farming adoption is a necessary condition for agricultural development in Malawi. Overtime, there have been lower adoption rates making Malawi one of the countries with an under developed dairy industry. Currently, little effort has been made to examine the determinants of adoption of any smallholder dairy farming. This study was conducted in all the three milk shed areas of the country using proportionate probability sampling to get a representative cross-section sample of dairy farming adopters and non-adopters. A sample size of 360 smallholder dairy farmers was randomly selected from different farming systems. An Average Treatment Effects Probit model was used to identify determinants of adoption. The study finds that adopters of dairy farming have higher incomes than non-adopters. Per capita income for adopters was K278000 compared to K86438 for the non-adopters. Further, dairy farming is mainly practiced by male headed households. It has also been found that formal education has positive effects on dairy farming adoption in the area. Household size and annual per capita expenditure also significantly affect adoption of dairy farming positively. Location of a milk bulking group in terms of region affects dairy farming adoption with Agricultural Development Divisions (ADDs) having high population such as the Southern region having high propensity to adoption of dairy farming. The study recommends a deliberate policy to increase dairy farming productivity to improve incomes of participating farmers and the country as a whole.

Key words: Dairy farming, adoption, Probit model, Malawi.

INTRODUCTION

According to the Department of Animal Health and Livestock Development (DAHLD) of the Ministry of Agriculture and Food Security (MoAFS), livestock production contributes positively to the economy of Malawi, accounting for about 11% of Malawi’s Gross Domestic Product (GDP) (DAHLD, 2005). Livestock also contributes to food and non-food uses (Freeman et al., 2009). Freeman et al. (2009) report that some districts in Malawi have livestock farming as their second most important livelihood activity after crop production. In most peri-urban areas, some farmers keep dairy animals on smallscale for food and income generation. The actual and potential contribution of animal agriculture to food security, sustainable livelihoods and agricultural development in Malawi is higher than depicted in provision of meat and milk (Banda, 2008).

Livestock breeds kept in Malawi are mostly local breeds. The population of animals is approximately 970,000 cattle of which 35,000 are dairy cattle, 3,600,000 are goats, 400,000 are sheep, 900,000 are pigs and 35 million are chickens (Ministry of Agriculture and Food Security, 2009). Banda (2008) states that the consumption of meat in Malawi is very low in that it is estimated at 9.45 kg/capita/annum, which represents an increase in meat consumption of 73.7% in 6 years since 2002. However, Malawi’s meat consumption is less than that of the Southern Africa Development Community (SADC) region of 15 kg/capita/annum. Milk consumption

*Corresponding author. E-mail: wglipita@hotmail.com.

is also relatively low estimated at 5 kg/capita/annum compared to those of Sub-Saharan Africa and Kenya which is estimated at 31 kg and 111 kg/ capita/ annum respectively (FAO, 2005). The low milk consumption is attributed to low production due to several social, economic and technical factors, including poor management, especially poor feeding and low numbers of dairy animals (Chindime, 2008).

Livestock products take a reasonable proportion on food budget expenses; monthly expenditure on food items in central Malawi accounts for 48-53% maize, 29.7% meats, 8.68% milk and eggs, 8.9% vegetables and 4.4% other foods (Banda, 2008). This shows that livestock products take about 39% of the food expenses which is substantial in the food budget.

The smallholder dairy sector plays an important role in the economy of Malawi and the livelihoods of farmers. The dairy programme originally concentrated mainly in the peri-urban areas of the three milk shed areas of Blantyre, Lilongwe and Mzuzu in order to access ready market and provide milk to urban areas where demand for milk was high. Infrastructure such as milk cooling facilities and processing plants were put in place to facilitate collection, processing and marketing of milk. Breeding and artificial insemination (AI) facilities were provided. Government employed and trained AI technicians who were serving the dairy crosses to upgrade the blood level of the progenies born from the dairy crosses. The technicians were provided with equipment and motorcycles to facilitate this activity. Apart from AI technicians, Dairy Development Assistants (DDAs) were deployed to provide training to farmers on good dairy husbandry practices (Agyman and Nkhonjera, 1984).

Initially, farmers were identified by the dairy extension workers and organized in clusters referred to as milk bulking groups (MBGs). The MBGs facilitated easy farmer training, message delivery and milk collection. Farmers were trained for two weeks on dairy farming and management and were required to plant pastures and build animal housing and milking facilities before receiving the cows. This ensured that the dairy animals were provided with adequate feed and housing facilities and were managed properly to produce adequate milk. Farmers who met the requirements set by livestock experts and received training were given two half-bred dairy crosses which were tested and assessed to attain minimum production levels of 5 L/day. Laws and regulations were developed by Government on milk production, collection, processing and marketing to protect the producers, processors and consumers and guide dairy stakeholders on ways to conduct business.

The milk produced was collected and processed in the dairy plants established and managed by Government parastatals according to Government of Malawi (GOM) (1995). The MBGs were organized in the three milk-shed areas and regional associations were set up to facilitate t he development of the dairy industry in the country. This led to the formation of Shire Highlands Milk Producers Association (SHIMPA) for the Southern Region; Central Region Milk Producers Association (CREMPA); Mpoto Dairy Farmers Association (MDIFA) for the Northern Region; and the national association known as Malawi Milk Producers Association (MPA) to oversee the activities of the regional associations.

Demand for milk due to urbanisation, population growth and improved income has led to establishment of dairy units in many parts of the country which are not the main urban areas. For example, dairy production is taking place in several areas in order to produce milk to supply their respective centres. These include Mwanza, Shire Valley and Mangochi in southern Malawi; Salima, Dowa, Kasungu, Ntchisi and Mchinji in central Malawi; and Mzimba, Karonga, Rumphi and Chitipa in northern Malawi. The expansion has also been attributed to Non-Governmental Organisations (NGOs) working in the dairy sector through participation in the delivery of dairy extension messages, distribution of animals and construction of milk cooling tanks. During the past nine years, attempts have been made in Malawi by NGOs such as Small Scale Livestock Promotion Programme (SSLPP) and Land ‘o' Lakes (L ‘o' L) in dairy development to encourage the dissemination of improved technologies on credit (Chindime, 2008). These efforts are complemented by the generation of technologies and messages by Government through the Departments of Agricultural Research Services (DARS) and DAHLD. Some of the technologies included provision of messages on supplementary feeding and homemade dairy rations, pasture establishment and fodder conservation, importation of dairy cattle for distribution to farmers on heifer pass-on loan scheme, construction of appropriate housing and structures for dairy animals, and provision of training to dairy farmers.

According to MoAFS and Agricultural Production Estimates (APES), there are about 15,000 smallholder dairy farmers in the country organized into MBGs (MoAFS, 2010). These farmers keep about 35,000 dairy cattle producing 10 liters/day on average. Some farmers with good management standards produce as much as 40 liters/animal/day (DAHLD, 2007). The dairy breeds being kept are mostly crosses between Malawi Zebu and Friesians. There are a few farmers keeping pure Friesian dairy cattle. There are also a few pure breeds of Jerseys, Ayrshires and others kept by some estates.

Despite these efforts made by Government and NGOs, the country is not self-sufficient in milk and dairy products. Dairy production remains low amongst smallholder farmers. Inadequacies in institutional and policy regulatory framework, limited use of sound technological factors (breeding, housing, feeding, disease control), socioeconomic factors, weak marketing infrastructure and inadequate capacity have greatly hampered the growth of the dairy industry in Malawi. This has adverse implications on household income, food security and nutrition.

This paper uses an Average Treatment Effects (ATE) Probit model to assess factors that affect dairy farming adoption in Malawi. Specifically, it analyzes socioeconomic factors affecting the adoption of dairy innovation amongst smallholder farmers. In addition, it compares the incomes and food security status between dairy and non-dairy farmers.

THEORETICAL FRAMEWORK

In the beginning of the analysis, the "classic" Probit model was used because its likelihood function is well behaved as it gives consistent Maximum Likelihood Estimate (MLE) coefficients (β) and the standard error of the estimate (s) (Maddala, 1992). The Probit model estimates the probability of participating in dairy farming for household level data and measures this likelihood after controlling the relevant variables used in the adoption model. The dependent variable in the first step is defined as a dichotomous variable with the values 1 for dairy farmers and 0 for non-dairy farmers.

The Probit model is applied in practice by the expression below:

$$Prob(y = 1) = f(x' and\ \beta') \quad \text{.................................(1)}$$

where x' is a vector of explanatory variables and β' are unknown parameters to be estimated. The probability function of the Probit model is usually the standard normal density which provides predicted values within the range of (0, 1).

In the Probit model, elasticity of decision to participate in dairy farming is estimated. The Probit model appears in Equation (1) by using the first two specifications for the distribution of being a participant or $y = 1$.

$$\Pr(y = 1) = \Phi(\beta' x) = \int_{-\infty}^{\beta' x} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2} z^2\right) dz \quad \text{..(2)}$$

$$\Pr(y = 0) = 1 - \Phi(\beta' x) \quad \text{..(3)}$$

$$E(y|x) = 0 \times \left(1 - \Phi(\beta' x)\right) + 1 \times \Phi(\beta' x) = \Phi(\beta' x) \quad \text{............................(4)}$$

where x is a $k \times 1$ vector of explanatory variables and β is a $k \times 1$ vector of unknown parameters to be estimated. The Φ is the standard normal cumulative distribution function.

The last equation is used to calculate the average change in E(y|x) with respect to the k^{th} (price) variable:

$$\frac{\partial E(y|x)}{\partial x_k} = \frac{\beta_k}{\sqrt{2\pi}} \exp(-\frac{1}{2} (\beta' x)^2) \quad \text{..................................(5)}$$

The derivative of E(y|x) with respect to x_k varies with the level of x_k and the other variables in the model. Therefore, the derivatives are evaluated at the mean values of all the x-variables in the sample. Then, the elasticity (at the means) of E(y|x) with respect to the kth variable are calculated with the following formula:

$$\frac{\partial E(y|x)}{\partial x_k} \frac{\bar{x}_k}{E(y|x)} = \frac{\beta_k}{\sqrt{2\pi}} \exp(-\frac{1}{2} (\beta' \bar{x})^2) \frac{\bar{x}_k}{E(y|x)} \quad \text{..............(6)}$$

where β^{th} are the coefficient on the k^{th} variable; E(y|x) is the average value of the y-variable. For example, supposing y_i assumes the value of 1 if household i participates in dairy farming, and the value of 0 if household i did not participate in dairy farming; then, E(y|x) is the percentage of dairy farmers in the sample, $\bar{x}_k$ is the average value of the k^{th} variable and $\beta '\bar{x}$ is equal to:

$$\beta_0 \bar{x}_0 + \beta_1 \bar{x}_1 + \beta_2 \bar{x}_2 + \cdots + \beta_k \bar{x}_k \quad \text{............................(7)}$$

where the "bars" represent sample averages (or mode) of the underlying variables such as income, household size, age, and sex.

Average Treatment Effects (ATE) were used to assess adoption rates. This method is relevant because a very small proportion of the farming population is exposed to dairy farming technologies. Literature reiterates that commonly used estimators of adoption yield inconsistent biased estimates due to non-exposure and/or selection bias. These biases make interpretation of estimates on adoption rates extremely difficult especially when diffusion of the technology is incomplete (Simtowe et al., 2010; Diagne and Demont, 2007; Besley and Case, 1993; Saha et al., 1994; Dimara and Skura, 2003). The non-exposure bias results from the fact that farmers who have not been exposed to a new technology cannot adopt it even if they might have done so if they had known about it (Diagne and Demont, 2006).

Wooldridge (2002) indicates that the true population adoption rate corresponds to what is defined in the modern treatment effect literature as the *Average Treatment Effect,* commonly denoted by ATE. The ATE parameter measures the effect or impact of a "treatment" on a person randomly selected in the population. Simtowe et al. (2010) report that in the adoption context, "treatment" corresponds to exposure to a technology and the ATE on the adoption outcomes of population members is the population mean adoption outcome. This is the population mean adoption outcome when all members of the population have been exposed to a technology and it is, therefore, a measure of the intrinsic value of the technology as indicated by its potential demand by the population. In that sense, the population mean adoption outcome measured by the ATE parameter is the population mean *potential* adoption.

The difference between the population mean potential adoption outcome and the population mean actual (that is, observed) adoption outcome, which is in fact the combined mean of population exposure to and adoption of the technology, is the population non-exposure bias, also known as the population adoption gap, which exists because of the incomplete diffusion of the technology in the population (Diagne and Demont, 2007). Similarly, the mean adoption outcome in the exposed subpopulation corresponds to what is defined in the treatment effect literature as the average treatment effect on the treated (that is, the mean effect of a treatment in the treated subpopulation), commonly denoted as ATE1 or ATT (Wooldridge, 2002). The difference between the population mean adoption outcome (ATE) and the mean adoption outcome among the exposed (ATE1) is the population selection bias (PSB). The consistent estimation of ATE and ATE1, which are the main focus of the treatment effect methodology, requires controlling appropriately for the exposure status. The details of the estimation procedures of the ATE parameters in the adoption context are given in Diagne and Demont (2007).

As Dehejia and Wahba (1998) proposed, let p(Xi) be the probability of a unit *i* having been assigned to treatment, defined as:

$$p(X_i) \equiv \Pr(T_i = 1|X_i) = E(T_i|X_i) \qquad (8)$$

Then:

$$(Y_{i1}, Y_{i0}) \perp\!\!\!\perp T_i|X_i$$

This also implies that:

$$(Y_{i1}, Y_{i0}) \perp\!\!\!\perp T_i|p(X_i).$$

Therefore, given that the treatment, T_i, is equal to 1 if subject *i* is participating in dairy farming and 0 if not, let $Y_i(1)$ be the outcome of dairy farming participation variables under treatment and $Y_i(0)$ in the counterfactual group, that is, non-dairy farmers.

Then Y_i and T_i can be observed where $Y_i = [T_i * Y_i(1) + (1-T_i) * Y_i(0)$. In turn, the treatment effect for each *i* is $Y_i(1) - Y_i(0)$ and the ATE is $ATE(x) = E[Y_i(1) - Y_i(0)]$; this can also be the difference in outcomes from participating in dairy farming relative to a control area for a person or unit *i* randomly drawn from the population. As Simtowe et al. (2010) reports, this model is estimated using the parametric conditional expectation $\Pr(T_i = 1|X_i) = E(T_i|X_i, w = 1)$ where T_i, x and w are observed variables. Then:

$$E(T_i|X_i, w = 1) = g(x, \beta)$$

where g is a known (possibly non-linear) function of the vector of covariates *x* and the unknown parameter vector *β* which is to be estimated using standard Least Squares (LS) or Maximum Likelihood Estimation (MLE) procedures using the observations (y_i, x_i) from the subsample of exposed farmers only with *y* as the dependent variable and *x* as the vector of explanatory variables.

With an estimated parameter $\hat{\beta}$, the predicted values $g(x, \hat{\beta}_i)$ are computed for all the observations *i* in the sample (including the observations in the non-exposed subsample) and ATE, ATE1 and ATE0 are estimated by taking the average of the predicted $g(x, \hat{\beta}_i)$ *i=1,..,n* across the full sample (for ATE) and respective subsamples (for ATE1 and ATE0):

$$A\hat{T}E = \frac{1}{n}\sum_{i=1}^{n} g(x_i, \hat{\beta})$$

$$A\hat{T}E1 = \frac{1}{n_e}\sum_{i=1}^{n} w_i g(x_i, \hat{\beta})$$

$$A\hat{T}E0 = \frac{1}{n - n_e}\sum_{i=1}^{n} (1 - w_i) g(x_i, \hat{\beta})$$

The effects of the determinants of adoption as measured by the *K* marginal effects of the *K* dimensional vector of covariates *x* at a given point $\bar{x}$ are estimated as:

$$\frac{\partial E(y_1|\bar{x})}{\partial x_k} = \frac{\partial(\beta'\bar{x})}{\partial x_k} \quad k = 1, \ldots, K$$

where x_k is the *kth* component of *x*.

The determinants of dairy farming adoption can be modeled using the aforementioned parametric assumptions of the Probit model. Further, the marginal effects of the ATE Probit model are also computed in a similar way only that the Probit model is now restricted to the exposed sample.

Several sources of literature on adoption such as Mendola (2007), Feder and Umali (1993) and Cornejo and McBrid (2002) review some determinants of technological adoption in agriculture. They conclude that demographic factors, wealth indicators, social status and information access variables play an important role in determining factors influencing adoption of technologies by smallholder farmers. This study, therefore, took some of these variables into account in modeling.

DATA SOURCES

The study was conducted within the milk shed areas of

Table 1. Sample sizes by farmer type, bulking group and milk shed area.

ADD/Milk shed area	Sample bulking groups	Sample size		
		Dairy	Non-dairy	Total
Mzuzu	Doroba	12	10	22
	Kapacha	14	0	14
	Kabvuzi	12	16	28
	Kawindula	11	21	32
Lilongwe	Chitsanzo	26	14	40
	Lumbadzi,	18	19	37
	Machite	17	20	37
Blantyre	Chandamale	17	32	49
	Chileka	8	1	9
	Tchoda,	12	16	28
	Mangunda	17	15	32
	Mpemba	16	16	32
Total		180	180	360

Table 2. Socioeconomic variables used in the model and their expected signs.

Variable	Description	Unit of measurement	Transformation	Expected sign
AGE	Age of the household head	Years	Natural log	+
EDU	Education of the household head	No. of years progressively spent in school	Natural log	+
HHSIZE	Household size	No. Individuals	Natural log	-
LAND	Land holding size	Hectares	Natural log	+
INCOME	Annual income	Malawi Kwacha	Natural log	+
GENDER	Gender of household head	1=male; 0=female	Dummy variable	+/-

Blantyre, Lilongwe, and Mzuzu. The bulking groups selected were Doroba, Kapacha, Kabvuzi and Kawindula in Mzuzu Agricultural Development Division (ADD), Chitsanzo, Lumbadzi, Machite in Lilongwe ADD, Chandamale, Chileka, Tchoda, Mangunda and Mpemba in Blantyre ADD. Proportionate probability sampling was used to get a representative cross-section sample of dairy farming adopters and non-adopters. A sample of 180 dairy and 180 non-dairy farmers were randomly sampled and were interviewed using a semi structured questionnaire (Table 1).

Data analysis

The data were analyzed using STATA 10.0 to produce descriptive and inferential statistics. The dependent variable in the empirical model is whether or not the farmer adopts dairy farming or not. This is explained by a number of socioeconomic variables namely, age of the household head, education level of the household head, household size, land holding size and annual income. Table 2 summarizes the variables used in the model.

RESULTS AND DISCUSSION

Descriptive analysis of socioeconomic factors affecting dairy farming adoption

The mean overall household size of the farmers was 5 persons (Table 3) which is similar to the national household size of a farm family in Malawi (MoAFS, APES, 2009). About 29% of the dairy farmers had some secondary school education (Forms 3 and 4). On the contrary, more than 37% of the non-dairy farmers had senior primary school education (Standards 6 - 8). Overall, 29% of the farmers had primary education, and dairy farmers were more educated than non-dairy farmers. Farming is the main occupation of about 94% of farmers with less than 5% in both cases sharing formal employment and business.

Approximately, 79% of dairy farmers lived in burnt brick houses while about 21% lived in mud homes. About 58%

Table 3. Socioeconomic characteristics of dairy and non-dairy farmers.

Variable	Type of farmer		Overall (%)	Chi-Square
	Dairy (%)	Non-dairy (%)		
Education level of household head				23.07
No school	5	8.3	6.7	
Std 1-5	17.8	19.4	18.6	
Std 6-8	21.7	37.2	29.4	
Form 1-2	20	17.2	18.6	
Form 3-4	29.4	15	22.2	
Tertiary	6.1	2.8	4.4	
Occupation of household head				6.58***
Farming	95	92.8	93.9	
Working	2.8	5	3.9	
Business	1.1	2.2	1.7	
Type of housing material				
Burnt bricks	79.4	58.9	69.2	
Mud wall	20.6	40.6	30.6	
Type of roofing material				1.86
Grass	36.1	52.2	44.2	
Iron sheet	61.7	47.8	54.7	
Tiles	1.1	0.0	1.1	
Gender of household head				4.36**
Male	72.2	72.2	72.2	
Female	28.8	28.8	28.7	
Food security				1.47
Secure (at harvest)	54.4	33.3	56.1	
Insecure (at harvest)	45.6	66.7	43.9	
Secure (December)	26.7	12.8	19.7	
Insecure (December)	73.3	87.2	80.3	
	Mean (SD)	Mean (SD)	Mean (SD)	Difference
Income (Malawi Kwacha)	278000.00 (248143.00)	86438 (113526)	364438 (361669)	165213.20***
Expenditure (Malawi Kwacha)	163986.00 (155189.00)	113526 (83212)	277512 (238401)	92401.66***
Land holding size (hectares)	3.385827 (1.436659)	4.05 (1.029932)	3.54491 (1.378542)	0.6641732***

Note: Mean differences were tested using two-sample t-test.
Source: Field Survey (2011).

of non-dairy farmers lived in burnt brick houses, while 30% lived in mud homes. Over 36% of all dairy farmers lived in grass thatched houses, while slightly over 62% lived in houses with roofs made of iron sheets and tiles. The majority of non-dairy farmers (52%) lived in grass thatched houses, while 48% lived in houses with roofs made of iron sheets; none of the non-dairy farmers lived in tile thatched houses. Dairy farmers lived in better homes than non-dairy farmers indicating that dairy farming improves income levels of households since the materials used such as iron sheets, burnt bricks and tiles are expensive.

Table 4. Determinants of the probability of exposure to dairy farming technology.

Variable	Coefficients		Marginal effects	
	Coef.	**Std. Err.**	**dy/dx**	**Std. Err.**
Gender of household head (if male)	-0.1254806	0.1682377	0.0387947	0.05097
Household size	0.0535697**	0.0309923	0.0168832**	0.0098
Total annual expenditure	4.24e-06***	7.60e-07	1.34e-06***	0.00000
Selling through MBG	1.696769***	0.5488029	0.378743***	0.07898
Selling to one institution	1.092144**	0.5556016	0.2763644***	0.10286
Milk Bulking Group (if in Lilongwe)	-1.223442***	0.3905436	-0.4515956***	0.13898
Type of homes (if iron sheet and burnt brick)	0.3614983**	0.1653823	0.1192876**	0.05735
Food Security (if secure by December)	0.1067189	0.1519456	0.0336338	0.04793
Landholding size	0.1399312***	0.0505402	0557428***	0.02013
Radio	0.2301643	0.1584571	-0.2301643	0.1584571
Constant	-1.07698	0.317541		
Number of interviews	465			
Pseudo R^2	0.35			
Log likelihood χ^2_8	216.55			

Source: Field Survey (2011).
Key: *p<0.10; **p<0.05; ***p<0.01.

On asset holdings, dairy farmers have more assets than their non-dairy counterparts. As Table 3 further shows, 72% of dairy farmers own bicycles for ease of transportation to markets. Only 50% of the non-dairy farmers possess bicycles. Access to information is also very vital in dairy farming and possession of radios leads to acquiring good information about markets. About 79% of the dairy farmers had radios compared to 60% of those that did not have radios. Possession of radios and dairy farming relationship was tested using chi-square and was significant at 10%. Noteworthy, dairy farmers spend more than non-dairy farmers. For instance, dairy farmers spend about MK164,000.00, while non-dairy farmers spend approximately MK114,000.00. Results are supported by Student t-tests which indicate high statistical significance between the two variables at 5% critical level.

About 54% of the households in dairy farming were secure during harvest season, while 46% reported that they became food insecure during harvest. Around December, when the rain begins, food is scarce and most houses become food insecure. Approximately, 73% of dairy farmers are food insecure from their own source. The situation worsens in non-dairy farmers as only 20% is food secure during this period.

Determinants of exposure to dairy farming

The descriptive analysis outlined above provides evidence that dairy farming improves household wellbeing. However, it does not inform about the determinants of dairy farming adoption in Malawi. In this study, about 61% of the sample households were exposed to dairy farming. Based on this information, a Probit regression of factors that affect the propensity of exposure to dairy was estimated. Table 4 depicts results from a Probit estimation of the determinants of the probability of getting exposed to dairy farming. Several variables such as income, expenditure, occupation of household head and land holding size show statistically significant coefficients at 1% level. The coefficient for household size is positive and significant at 5% indicating that the more adults a household has, the higher the propensity for being involved in dairy farming. This is so because large household sizes ensure availability of labour on the farm. Total annual expenditure, a proxy for income, also had a significant coefficient at 1%. This implies that households with higher income levels have high propensity for participating in dairy farming. Furthermore, indicating livelihood status, the type of building material of respondents' houses also positively influences the propensity to participate in dairy farming. This variable was statistically significant at 1%.

Presence of policies and a regulatory framework and an enforcing mechanism in dairy farming increases the propensity of participating in dairy farming. This is evidenced by a positive coefficient on whether or not there exists a rule that forces farmers to sell their milk products through Milk Bulking Groups.

Selling through one institution increases the propensity of getting involved in dairy farming. This is evidenced by a positive sign, significant at 1%, in the variable. Noteworthy, location of the Milk Bulking Groups (MBGs) affect the propensity to participate in dairy farming. Distance to milk selling place may influence the propensity to go into dairy farming as long distances may discourage farmers from participating in dairy farming.

Table 5. Comparison of regression results of ATE and Classic Probit models.

Variable	ATE Probit model		Classic Probit model	
	Coef.	Std. Err.	Coef.	Std. Err.
Gender of household head (1 = male, 0 = female)	-0.0090658	0.2350568	-0.1254806	0.1682377
Household size	0.0347918	0.0418159	0.0535697**	0.0309923
Total annual expenditure	4.88e-06***	1.26e-06	4.24e-06***	7.60e-07
Selling through MBG	1.270989**	0.5727411	1.696769***	0.5488029
Selling to one institution	1.191134**	0.5826722	1.092144**	0.5556016
Milk Bulking Group (if in Lilongwe)	-0.6729198	0.613085	-1.223442***	0.3905436
Type of homes (if iron sheet and burnt brick)	0.5126436**	0.2121406	0.3614983**	0.1653823
Food Security (if secure by December)	0.0372638	0.2034662	0.1067189	0.1519456
Landholding size	0.3815816***	0.0828383	0.1399312***	0.0505402
Radio ownership	0.0016704	0.2469115	0.2301643	0.1584571
Constant	0.7337453	0.6733541	-1.07698	0.317541
Number of interviews	465		465	
Pseudo R^2	0.3269		0.35	
Log likelihood χ^2_{10}	189.26		216.55	

Source: Field Survey (2011).
Key: *p<0.10; **p<0.05; ***p<0.01.

For example, farmers in Lilongwe MBGs showed negative propensity at 1% as in many places in Lilongwe ADD bulking groups are far apart and away from the tarmac road network.

Food security status of the individuals, albeit statistically insignificant, also positively affects the propensity to adopt dairy farming technologies in the sampled areas. For instance, if households are food secure during lean periods, they may have options to invest in other technologies such as dairy farming.

Determinants of smallholder adoption of dairy farming technologies

Table 5 presents results on the determinants of dairy farming adoption for the classic “adoption” model, and ATE Probit model. There are remarkable differences in the magnitude of the coefficients as well as their marginal effects between the two models. In general, the marginal effects of the ATE Probit model are smaller in absolute values than those of the classic “adoption” model. The observed findings are consistent with the theoretical expectation as reported by Diagne and Demont (2007) and Simtowe et al. (2010); the conditional mean “adoption” function estimated in the classical adoption model is equal to the true population average conditional adoption function (the “true” population adoption function) multiplied by the probability of being aware of the technology. As Simtowe et al. (2010) reports, for a factor determining adoption alone and not awareness, its marginal effect calculated from the classical “adoption” model is equal to its marginal effect from the true adoption model multiplied by the conditional probability of awareness, a quantity always between 0 and 1 and usually very small when not many farmers are aware of the technology.

Except the ATE coefficients are quite smaller than the “classic Probit model, the results are similar to smallholder adoption studies carried out by Simtowe et al. (2010) and Mendola (2007). Most variables are significant in both cases of large Log likelihood estimates of 189.6 and 216.55 in the ATE Probit model and the “classic” Probit model respectively.

The size of the land owned by the household returned a positive and significant coefficient suggesting that farmers with larger holdings are more likely to adopt dairy farming and new agricultural technologies than those with smaller farms (Table 6). The ownership of a radio returned a positive coefficient but not a significant coefficient. Having radios in a household may increase the household’s propensity to adopt new technologies since houses which have such assets can acquire information quite easily. It may also be a sign of wealth as purchasing of radios requires money. Economic constrain paradigm of adoption models states that input fixity in the short run, such as access to credit, land, labor or other critical inputs, limits production flexibility and conditions technology adoption decisions (Uaiene et al., 2009). This is why most of the wealth related variables returned positive signs.

Variables capturing access to markets such as existence of rules enforcing farmers to sell milk products to one institution and location of a milk bulking group showed significance at five percent and returned their expected outcomes. Mostly, new institutional literature suggests that existence of a regulatory framework to

Table 6. Comparison of marginal effects of variables using ATE and Classic Probit models.

Variable	ATE Probit		Classic Probit	
	dy/dx	Std. Err.	dy/dx	Std. Err.
Gender of household head (if male)	-0.0013104	0.0339	0.0387947	0.05097
Household size	0.0050421	0.00604	0.0168832**	0.0098
Total annual expenditure	7.07e-07***	0.00000	1.34e-06***	0.00000
Selling through MBG	0.1557914**	0.06541	0.378743***	0.07898
Selling to one institution	0.1460304**	0.06435	0.2763644***	0.10286
Milk Bulking Group (if in Lilongwe)	-0.1403158	0.1671	-0.4515956***	0.13898
Type of homes (if iron sheet and burnt brick)	0.0873634*	0.04546	0.1192876**	0.05735
Food Security (if secure by December)	-0.0054004	0.0295	0.0336338	0.04793
Landholding size	0.0553001***	0.01495	0557428***	0.02013
Radio ownership	0.0002421	0.03578	-.2301643	0.1584571
Number of interviews	465		465	
Pseudo R^2	0.35			
Log likelihood χ^2_{10}	189.26		216.55	

Source: Field Survey (2011).
Key: *p<0.10; **p<0.05; ***p<0.01.

facilitate exchange and order in marketing reduces transaction costs (Williamson, 1981). Transaction cost literature also suggests that farmers who have a ready market for their products reduce search costs (North, 1994). However, in Malawi, location of the milk bulking group has significant effects on how farmers behave. It should be noted that farmers close to markets, for example, in peri-urban areas would rather sell their milk products directly to consumers. This is perhaps why location of an MBG (if it is in Lilongwe, a peri-urban area) returned a negative sign.

Food ranks first in Maslow's hierarchy of needs and one of the key cornerstones of the Malawi Growth and Development Strategy (MGDS) is food security. Although not statistically significant, farmers who have ready access to food even in lean seasons, for example December, have a higher propensity to adopt dairy farming than those that do not.

CONCLUSION AND RECOMMENDATIONS

This paper has analyzed socioeconomic factors that affect adoption of dairy farming in Malawi. It has been observed that estimates of the classic Probit model overstate the extent of adoption in Malawi. However, the Average Treatment Effects Probit model produces consistent and accurate estimates of the determinants of dairy farming adoption. The study has shown that household size, gender, total annual expenditure, milk products selling regulations and milk bulking group location affect adoption of dairy farming. Descriptive analysis showed that dairy farmers were on average better off in the aforementioned socioeconomic factors. By large, small holder dairy farming is not practiced by a lot of farmers across Malawi.

The study recommends that development and investment policies need to consider dairy farming as one of the strategies in poverty reduction. The factors that affect the implementation and adoption of the dairy industry need to be addressed to improve the performance of the industry. To be inclusive in development, issues of gender, household size and income need to be addressed to improve the adoption and performance of the industry, and policy issues affecting such issues need to be addressed to promote the dairy industry apart from other technical and socio-economic issues.

REFERENCES

Banda JW (2008). Revolutionising the Livestock Industry in Malawi. The 12th University of Malawi Inaugural Lecture, Crossroads Hotel, Lilongwe, Malawi.

Besley T, Case A (1993). Modeling Technology Adoption in Developing Countries" The American Economic Review, Vol. 83, No. 2, Papers and Proceedings of the 105 Annual Meeting of the American Economic Association. pp. 396-402.

Chindime S (2008). The role of credit on the productivity and adoption of improved dairy Community welfare. M.SC. Thesis. Bunda College of Agriculture, University of Malawi. Lilongwe, Malawi.

Dehejia R, Wahba S (1998). Propensity Score Matching Methods for Nonexperimental Causal Studies," NBER Working Paper No. 6829.

Department of Animal Health and Livestock Development (DAHLD) (2007). Annual Report. Lilongwe, Malawi. pp 1-65.

Department of Animal Health and Livestock Development (DAHLD) (2005). Policy Document on Livestock in Malawi. Lilongwe, Malawi pp 7-8.

Diagne A, Demont M (2007). Taking a New look at Empirical Models of Adoption: Average Treatment Effect estimation of Adoption rate and its Determinants. .Agric. Econ., Vol.37. pp30.

Diagne A, Demont M. (2006). Diffusion and adoption of NERICA rice varieties in Côte d'Ivoire. The Developing Economies, XLIV-2 (2006) pp. 208-31.

Dimara E, Skuras D (2003). Adoption of agricultural innovations as a two-stage partial observability process. Agric. Econ., 28: 187-196.

Feder G, Umali D (1993). The Adoption of Agricultural Innovations: A Review of Technological Forecasting and Social Change 43: pp215-239.

Food and Agriculture Organisation (FAO) (2005). http//www.faostat. external.fao.org (Accessed, July 2005).

Freeman HA, Kaitibie S, Moyo S, Perry BD (2009). Livestock, livelihoods and vulnerability in Lesotho, Malawi and Zambia: Designing livestock interventions for emergency situations. International Livestock Research Institute. Research Report.

Government of Malawi (1995). Agriculture and Livestock Development strategies and Action Plan. Lilongwe, Malawi.

Maddala GS (1992). Introduction to Econometrics, 0138803528, 9780138803520, Prentice-Hall International.

Mendola M (2007). Agricultural technology adoption and poverty reduction: A propensity-score matching analysis for rural Bangladesh. Food Policy, 32(3), 372–393.

Ministry of Agriculture and Food Security (MOAFS) (2009). Agricultural Production Estimates. Lilongwe, Malawi pp1-6.

Ministry of Agriculture and Food Security (MOAFS) (2010 a). Agricultural Production Estimates. Lilongwe, Malawi. pp1-8.

Ministry of Agriculture and Food Security (MOAFS) (2010b). Agriculture Sector Wide Approach (ASWAP), Lilongwe, Malawi pp5-24.

Ministry of Agriculture and Food Security Technical Secretariat, (2009). Manual on Food Security assessment, Lilongwe, Malawi. Pp15-35.

North D (1994). Performance through Time. *American Economic Review.*84 (3): nutritional impacts of market-oriented dairy production in the Ethiopian highlands. Socio-economic and Policy Research Working Paper 51I. International Livestock Research Institute (ILR), Nairobi, Kenya. pp 27.

Saha L, Alan LH, Robert S (1994). Adoption of emerging technologies under output

Simtowe F, Bekele S, Tsedeke A, Muricho G (2010). Socioeconomic Assessment of Baseline Pigeon Pea and Groundnut Production Conditions, Farmer Technology Choice, Market Linkages, Institutions and Poverty in Rural Malawi.

Uaiene RN, Arndt C, Masters, WA (2009). Determinants of Agricultural Technology Adoption in Mozambique. Discussion papers No. 67E. Accessed athttp://www.mpd.gov.mz/gest/documents/67E_AgTechAdoptionMoz.pdf.

uncertainty". American Journal of Agricultural Economics. 76: 836-846.

Williamson OE (1981). The Economics of Organization: A Transaction Costs Approach. The Am. J. Sociol., 87 (3) 548-577.