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Opportunity cost of adopting improved planted forage: Evidence from the adoption of *Brachiaria* grass among smallholder dairy farmers in Kenya

Kevin W. Maina*
International Livestock Research Institute – Kenya, Nairobi, Kenya; Department of Economic and Technological Change, Center for Development Research (ZEF)/Zentrum für Entwicklungsforschung, University of Bonn, Bonn, Germany. E-mail: mainakevin.km@gmail.com/K.Maina@cgiar.org

Cecilia N. Ritho
Department of Agricultural Economics, University of Nairobi, Nairobi, Kenya. E-mail: ceciliaritho@gmail.com

Ben A. Lukuyu
International Livestock Research Institute – Uganda, c/o Bioversity International, Kampala, Uganda. E-mail: b.lukuyu@cgiar.org

Elizaphan James O. Rao
International Livestock Research Institute – Kenya, Nairobi, Kenya. E-mail: j.rao@cgiar.org

* Corresponding author

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Abstract

Current global trends in population growth, urbanisation and a growing middle-class economy have resulted in increased demand for livestock and products, and more so dairy products. This necessitates the need for livestock producers to respond to the growing demand. However, farmers' efforts are aggravated by the effects of climate change. The need arises for a sustainable source of fodder to alleviate the situation, while at the same time offering farmers other opportunities to participate in fodder markets through the adoption of climate-smart Brachiaria *grass. In this article, the opportunity cost of producing* Brachiaria *in favour of Napier grass is estimated using household survey data obtained from dairy farmers in Kenya's drier agroecological zones. The study utilised full-information endogenous switching regression to compute the opportunity cost by comparing the gross margins generated from Napier and* Brachiaria *grass. The findings reveal that dairy farmers face a higher opportunity cost of their fodder land by producing Napier in favour of* Brachiaria, *given by the transitional heterogeneity of USD 79.74. Furthermore, the adoption of* Brachiaria *is determined by the age and experience of farmers in fodder production, by herd size, breed type, perception of milk productivity, group membership, and access to extension services. The results highlight the need for widespread adoption through extension and technical support to farmers. This would also enable farmers to participate in fodder markets and support their livelihood.*

Key words: *Brachiaria* grass; opportunity cost; gross margins; endogenous switching regression; planted fodder technology

1. Introduction

Continued economic growth and a change in consumer dietary preferences have led to an increase in demand for livestock products (Bosire *et al*. 2016a). Globally, it is projected that the number of urban dwellers will increase to 6.3 billion by the year 2050, and 90% of the projected increase will occur in Africa and Asia (United Nations 2015). It is expected that, with population growth, the demand for meat and milk products in Africa will double by the year 2050 (Holechek *et al*. 2016). In Kenya, the population is projected to reach 96 million by 2050, with over 50% of the population living in urban areas (FAO 2017). The ability of African nations to feed the growing population raises serious concerns.

Livestock production, specifically dairy, contributes significantly to the economy and livelihoods of farmers. Efficient milk production requires a regular supply of quality fodder in adequate quantities (Nangole *et al*. 2011). However, smallholder farmers are constrained by feed scarcity, which is associated with seasonality in rainfall, poor fodder production techniques and poor feed quality, and limited land for fodder production.[1] Therefore, the intensification of the livestock production system is one strategy for meeting the increased demand for milk. Intensification of livestock production requires sustainable fodder production systems, which are currently threatened by increased feed prices and prolonged drought (USAID 2015). Therefore, the production of improved planted forages is a solution that can be pursued to alleviate the current situation. Napier grass (*Pennisetum purpureum*), a common cut-and-carry forage option, is affected by smut disease and therefore may not be a sustainable source of feed. In addition, it has a protein content that is lower than what is necessary to support commercial dairy production (Njarui *et al*. 2016). More recently, the focus has shifted to climate-smart forages such as *Brachiaria* grass.

Brachiaria grass is a climate-smart[2] fodder promoted by stakeholders in the livestock sector as an alternative fodder source. Previous research on *Brachiaria* shows that it has high biomass production and nutritious herbage, and therefore has the potential to increase livestock productivity (Holmann *et al*. 2004). It can improve nitrogen-use efficiency, sequester carbon, as well as adapt to drought and soils with low fertility (Arango *et al*. 2014; Moreta *et al*. 2014; Rao *et al*. 2014).

The establishment of sustainable fodder systems would not only result in increased milk production, but also increased income from the sale of the fodder. There is evidence that the intensification of livestock production can increase the use of off-farm feed resources and spur the emergence of feed and fodder markets (Nangole *et al*. 2011; Bosire *et al*. 2016b).

Several studies have assessed the potential of *Brachiaria* grass as a forage option (Machogu 2013; Nguku 2015; Njarui *et al*. 2016). Despite the nutritional and productivity benefits of *Brachiaria* identified in these studies, little is known about its financial benefit as a fodder enterprise. Although Kassie *et al*. (2018) attempted to quantify the benefits of the grass in their study on push-pull[3] technology using *Brachiaria* grass as a push crop, they were unsuccessful because of the frequent harvesting of the fodder. The current study uses a gross margin analysis of *Brachiaria* as a fodder

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[1] In these circumstances, farmers provide feed in an opportunistic manner because they react to changes in feed supply, rather than accumulating feed stocks to minimise risk (Nangole *et al*. 2011).
[2] Climate-smart agriculture implies sustainable agricultural production while addressing the challenges of climate change (FAO 2013).
[3] Push-pull technology was developed by the International Centre for Insect Physiology and Ecology (ICIPE) as a conservation agriculture method to control for maize stem borer and striga weeds in maize production.

enterprise to quantify the financial benefits of adopting the grass. Understanding the potential financial benefit from *Brachiaria* fodder production will contribute to designing strategies for its widespread adoption.

The aim of this study was to provide empirical evidence of the financial benefit of *Brachiaria* to underscore the agribusiness opportunity it can create for farmers to diversify sources of farm income through fodder production. Feed and fodder markets can allow land-constrained farmers to produce milk sustainably without relying on their fodder production. Thus, *Brachiaria* grass technology would be contributing to Sustainable Development Goal 1, namely of 'ending poverty', and promote sustainable agricultural development (Ngoma 2018).

2. Materials and methods

2.1 Theoretical analysis of farmers adoption process

Farmers are rational and therefore aim to maximise their welfare, given specific constraints. This study adopted the theory of expected utility, whereby the decision by a farmer to adopt technology such as *Brachiaria* – given the risk and uncertainties of their biophysical environment – is based on a comparison of the expected utility of maximising profit (Schoemaker 1982). Kassie *et al*. (2015) note that farmers will adopt a technology if the expected utility of adoption (Ua) is greater than that of non-adoption (Un). The theory of expected utility has motivated several studies on farmers' decision-making (Oglethorpe 1995; Babcock & Hennessy 1996; Gómez-Limón *et al*. 2004).

Following Asfaw *et al*. (2012), the utility of adopting *Brachiaria* can be modelled as a link between the adoption decision and the expected benefits. Thus, the adoption decision is a dichotomous choice component that is determined by observable characteristics Z_i, and a stochastic error term, ε_i, which is unobservable (Greene 2003), such that:

$$I_i^* = \beta Z_i + \varepsilon_i, \quad I_i = 1\ if\ I^* > 0, \tag{1}$$

where I_i is a binary variable that equals 1 if household *I* adopts *Brachiaria*, and 0 otherwise; β is a vector of parameters to be estimated; Z_i is a vector of household characteristics; and ε_i is the error term. The error term is unobservable, hence it is assumed to be normally distributed.

The probability of adopting *Brachiaria* can then be estimated as follows:

$$\Pr(I_i = 1) = \Pr(I_i^* > 0) = 1 - D(-\beta Z_i), \tag{2}$$

where *D* is the cumulative distribution function for ε_i whose assumptions determine the functional form used in the estimation. In our case we applied the probit model (Green 2003).

2.2 Model specification

Following Wale *et al*. (2006), the opportunity cost approach was adopted to estimate the opportunity cost of growing *Brachiaria* in favour of Napier grass. The gross margin generated from *Brachiaria* grass (GM *Brachiaria* grass) is compared to that of Napier grass (GM Napier grass). In relation to the gross margin (GM) of *Brachiaria* as the next best alternative for use on farmers' fodder land, the opportunity cost is computed as follows:

$$OPPORTUNITY\ COST = (GM_{Brachiaria} - GM_{Napier\ Grass}) \tag{3}$$

The computation of the opportunity cost associated with adopting *Brachiaria* grass in place of Napier grass requires information on what *Brachiaria* farmers would have gained had they not adopted, and what Napier grass farmers would have earned had they adopted *Brachiaria*. The specification for the study assumes that one farmer cannot be observed growing both *Brachiaria* and Napier grass (Kassie *et al*. 2018; Ngoma 2018).

Moreover, selection bias may arise as a result of self-selection into adoption. Observable and unobservable covariates that simultaneously affect adoption and the outcomes could also lead to selection bias. Adopters and non-adopters may be different with respect to observable characteristics, such as proximity to inputs markets, education, extension access and resource endowment. However, unobservable characteristics such as managerial ability, self-motivation and business acumen may result in biased estimates of the true effect of technology adoption on the outcome variable (gross margins).

Sample selection renders the estimates using the ordinary least squares (OLS) method biased. An alternative method would be propensity score matching (PSM), but its implementation is likely to be hindered by the unobservable variables, which lead to self-selection into adoption. Another alternative method is the difference-in-difference method, which cannot be executed using the cross-sectional data available for this study (Wooldridge 2010). Therefore, endogenous switching regression (ESR) was used to overcome the selection bias, thus yielding consistent estimates of the opportunity cost of adopting *Brachiaria* based on actual and counterfactual outcomes (Lokshin & Sajaia 2004). ESR is a variant of the instrumental variable (IV) method and can overcome selection bias; it has also been used in other studies (Carter & Milon 2005; Di Falco & Bulte 2013; Teklewold *et al*. 2013; Abdulai & Huffman 2014; Shiferaw *et al*. 2014; Kassie *et al*. 2015).

The FIML-ESR uses a two-step estimation procedure to estimate treatment effects yielding consistent standard errors by simultaneously estimating the selection and outcome equations (Lokshin & Sajaia 2004; Semykina & Wooldridge 2010). In the first stage, the adoption decision is analysed using the probit model (selection equation), which also generates the inverse Mills ratio for controlling selection bias. The inverse Mills ratio is included as a regressor in the second stage, which applies an OLS method to estimate the opportunity cost of *Brachiaria* adoption. Thus, the selection equation is specified as follows:

$$I_i^* = \beta Z_i + \varepsilon_i \; with \; I_i = \begin{cases} 1 \; if \; \beta Z_i + \varepsilon_i > 0 \\ 0 \; otherwise \end{cases} \tag{4}$$

Variables are as defined in equation (1).

The socio-economic and household demographic characteristics used in the adoption equation are based on the adoption literature for agricultural technology (Wale *et al*. 2006; Abdulai & Huffman 2014; Khan *et al*. 2014; Shiferaw *et al*. 2014; Murage *et al*. 2015a; Kassie *et al*. 2018). Household characteristics such as sex of the household head, years of schooling completed, experience in dairy and fodder production and household size are likely to increase the adoption of *Brachiaria*. Khan *et al*. (2014) note that larger households headed by a woman who has higher education are likely to adopt new agricultural technologies to increase the productivity of their farms. More educated farmers tend to have requisite skills and a better understanding of new technologies. Asset endowment measured by land size and herd size as a productive resource is likely to increase the adoption of new technology, and more so fodder technologies, by livestock producers (Kassie *et al*. 2018). Farmers with access to credit facilities and who are members of agricultural or financial groups are likely to adopt new technologies. Consequently, access to extension services is likely to increase adoption, as these services expose farmers to new technologies (Murage *et al*., 2015a). Moreover, farmers' perceived attributes of technology are likely to increase adoption if farmers perceive that the technology will increase productivity (Murage *et al*. 2015b). Wale *et al*. (2006) note that farmers who produce cash crops would value technology that enhances productivity, and therefore this aspect would increase the likelihood of adoption.

The second stage involves estimating separate equations for each outcome (gross margins) for two regimes: *Brachiaria* grass farmers and Napier grass farmers (Rees & Maddala 1985):

$$Y_1 = \alpha_1 X_1 + \varepsilon_1 \; if I_i = 1, \tag{5}$$

$$Y_0 = \alpha_0 X_0 + \varepsilon_0 \; if I_i = 0, \tag{6}$$

where Y_1 and Y_0 are outcome measures (gross margins) for *Brachiaria* grass farmers and Napier grass farmers respectively. Gross margins were computed in Kenya shillings per acre per year, given that *Brachiaria* and Napier grass are harvested after growing for three to four months. Gross margins were computed as gross revenue of the respective fodder less variable costs of inputs. X_j $(j = 1{,}0)$ is a vector of covariates that affect the gross margins. The covariates include the same variables used in the selection equation. α_j $(j = 1{,}0)$ is a vector of parameters to be estimated, and ε_j is a vector of error terms.

Asfaw *et al*. (2012) caution that self-selection into adoption may result in nonzero covariance between the error terms of the selection equation, Equation (1), and the outcome equations, (5) and (6). Given the assumption of the endogenous switching framework of a trivariate normal distribution[4] with zero mean and nonzero covariance on the error terms, the matrix can be modelled as:

$$corr(\varepsilon_i \varepsilon_1 \varepsilon_0) = \Sigma = \begin{pmatrix} \sigma_\varepsilon^2 & \sigma_{\varepsilon\varepsilon1} & \sigma_{\varepsilon\varepsilon0} \\ \sigma_{\varepsilon1\varepsilon} & \sigma_{\varepsilon1}^2 & \sigma_{\varepsilon1\varepsilon0} \\ \sigma_{\varepsilon0\varepsilon} & \sigma_{\varepsilon0\varepsilon1} & \sigma_{\varepsilon0}^2 \end{pmatrix}, \tag{7}$$

where σ_ε^2, $\sigma_{\varepsilon1}^2$ and $\sigma_{\varepsilon0}^2$ are variances of the error terms from the selection and outcome equations respectively. $\sigma_{\varepsilon1\varepsilon}$ is the covariance between ε_i and ε_1, and $\sigma_{\varepsilon0\varepsilon}$ is the covariance between ε_i and ε_0. $\sigma_{\varepsilon1\varepsilon0}$ is the covariance between ε_1 and ε_0, but it is never defined because Y_1 and Y_0 are not observed simultaneously. Therefore, the expected values of the error terms for equations (5) and (6) are given by:

$$E(\varepsilon_1 | I_i = 1) = E(\varepsilon_1 | \varepsilon_i > -\beta Z_i) = \sigma_{\varepsilon1\varepsilon} \frac{\phi(\beta Z_i)}{\Phi(\beta Z_i)} = \sigma_{\varepsilon1\varepsilon}\lambda_1, \tag{8}$$

$$E(\varepsilon_0 | I_i = 0) = E(\varepsilon_0 | \varepsilon_i \leq -\beta Z_i) = \sigma_{\varepsilon0\varepsilon} \frac{-\phi(\beta Z_i)}{1-\Phi(\beta Z_i)} = \sigma_{\varepsilon0\varepsilon}\lambda_0, \tag{9}$$

where ϕ is a standard normal probability density function and Φ is a standard normal cumulative function. λ_1 and λ_0 are ratios representing the inverse Mills ratios for *Brachiaria* farmers and Napier grass farmers that are to be included in the outcome equations (5) and (6) (Wooldridge 2015).

Although the covariates in the selection and outcome equations overlap, we instrumented selection into the adoption of *Brachiaria* by group membership and perceptions of *Brachiaria*. These

[4] The trivariate distribution refers to error terms in the selection and two outcome equations of the endogenous switching regression.

instruments were omitted in the outcome equations (5) and (6). The instruments are related to access to information and have been used before by Abdulai and Huffman (2014).

2.3 Estimating the opportunity cost

In the second step, the inverse Mills ratios computed in the selection equation were incorporated into the outcome equation and specified as:

$$Y_1 = \alpha_1 X_1 + \sigma_{\varepsilon 1 \varepsilon}\lambda_1 + \mu_1 \quad if\, I_i = 1 \tag{10}$$

$$Y_0 = \alpha_0 X_0 + \sigma_{\varepsilon 0 \varepsilon}\lambda_0 + \mu_0 \quad if\, I_i = 0 \tag{11}$$

The endogenous switching regression model was estimated using the *movestay* Stata command of Lokshin and Sajaia (2004).

Following Kuntashula and Mungatana, (2013), we can estimate the opportunity cost from equations (10) and (11):

$$E(Y_1|I_i = 1) = \alpha_1 X_1 + \sigma_{\varepsilon 1 \varepsilon}\lambda_1 \tag{12}$$

$$E(Y_0|I_i = 0) = \alpha_0 X_0 + \sigma_{\varepsilon 0 \varepsilon}\lambda_0 \tag{13}$$

$$E(Y_0|I_i = 1) = \alpha_0 X_1 + \sigma_{\varepsilon 0 \varepsilon}\lambda_1 \tag{14}$$

$$E(Y_1|I_i = 0) = \alpha_1 X_0 + \sigma_{\varepsilon 1 \varepsilon}\lambda_0 \tag{15}$$

Equations (12) and (13) are the observed outcomes conditional on *Brachiaria* grass adoption and non-adoption. Equation (14) is the counterfactual outcome for Napier grass farmers had they adopted *Brachiaria* grass, whereas Equation (15) is the counterfactual outcome for *Brachiaria* grass farmers had they not adopted. The average treatment effect on the treated (opportunity cost for *Brachiaria* grass farmers/ATT) is the difference between equations (12) and (14) (Di Falco & Bulte 2013; Heckman 2017):

$$ATT = E(Y_1|I_i = 1) - E(Y_0|I_i = 1) = X_1(\alpha_1 - \alpha_0) + \lambda_1(\sigma\varepsilon_1\varepsilon - \sigma\varepsilon_0\varepsilon) \tag{16}$$

The opportunity cost for Napier grass farmers given by the average treatment effect on the untreated (ATU) is the difference between equations (15) and (13):

$$ATU = E(Y_1|I_i = 0) - E(Y_0|I_i = 0) = X_0(\alpha_1 - \alpha_0) + \lambda_0(\sigma\varepsilon_1\varepsilon - \sigma\varepsilon_0\varepsilon) \tag{17}$$

To determine if the opportunity cost of *Brachiaria* for adopters is greater or smaller than if they had not adopted, a transitional heterogeneity effect was computed, taking the difference between ATT and ATU. If the difference is zero, then adopters and non-adopters are the same in terms of the net returns.

3. Sampling and data collection

Data was collected from Siaya and Makueni counties as examples of the arid, medium-potential agro-ecological zones in Kenya where the Government of Kenya, and ILRI as a development partner, have promoted commercial dairy farming and *Brachiaria* adoption since 2015. The sampling targeted dairy farmers who had grown *Brachiaria* grass for at least twelve months. The gross margin calculated referred to at least a one-year cycle. For the control group, the study targeted dairy farmers in neighbouring villages who had planted Napier grass (*Pennisetum purpureum* (L.) Schumach.).

Multi-stage sampling was done in three stages. First, counties and sub-counties where dairy and fodder production was carried out were identified purposively. Second, in each sub-county, a list of farmers who had planted *Brachiaria* was compiled, along with another list of those who had not planted it. This was done with the help of extension officers and resource farmers. In the third stage, farmers were randomly sampled from each list using a proportionate to size approach, resulting in 132 farmers (57 *Brachiaria* grass farmers and 75 Napier grass farmers) in Makueni and 105 farmers (54 *Brachiaria* grass farmers and 51 Napier grass farmers) in Siaya, totalling 237 farmers. The data collected included demographic, socio-economic and institutional factors that affect the adoption of *Brachiaria*, along with a gross margin analysis for Napier and *Brachiaria* grass. Data was collected and entered using the computer-aided personal interviews application in the CS Pro version 7.1 program.

4. Results and discussion

4.1 Descriptive statistics

The average dairy farmer was 56 years old, with 10 years of formal schooling, heading a household of six members and had 10 to 12 years of experience in dairy and fodder production (Table 1). This implies that, on average, households had significant levels of human capital (physical and technical). The majority of households (77%) were headed by men. *Brachiaria* grass farmers were significantly older than Napier grass farmers at the 1% level of significance, suggesting that participation by the youth (35 years and below) in dairy farming in the Siaya and Makueni counties was still low. On average, farms were 3.62 acres and were owned with title deed by 62% of the farmers (Table 1). It was found that *Brachiaria* grass farmers had larger farms than Napier grass farmers, suggesting that a certain minimum land area was required to set up a fodder enterprise. Consequently, 40% of the farmers used part of their land for cash crops, such as sugarcane and sisal, thereby diversifying their farm income.

An average farmer had a herd size given by a tropical livestock unit (TLU) of 7.58 units. *Brachiaria* grass farmers had more livestock units than Napier grass farmers at the 1% level of significance. It was also found that *Brachiaria* grass producers had more exotic breeds than Napier grass farmers, who had more indigenous breeds. About 70% of the farmers derived their income from off-farm activities such as formal and informal employment and business. Forty-eight percent of the farmers acquired credit for both agricultural and personal use (Table 1). Farmers blamed the need for additional income on high interest rates on loans and payback plans that did not consider the unique characteristics of farming. Farming is characterised by seasonality and irregular cash flow, making monthly loan payments untenable. Adopters of *Brachiaria* had access to significantly more credit than non-adopters, suggesting they had higher resource endowment and were more able to adhere to the stringent requirements on loans.

About 73% of farmers belonged to social groups, and 63% received extension service on dairy and fodder production at least more than once in 2017/2018. Adopters received significantly more extension services than non-adopters. This implies that adopters have better access to information and social services, and higher social capital. Consequently, they had significantly higher perception scores on the benefits of *Brachiaria* compared to non-adopters.

On average, *Brachiaria* had a gross margin of USD 989.14 per acre annually, compared to an annual amount of USD 447.42 per acre from Napier grass, suggesting that *Brachiaria* is superior to Napier grass in terms of productivity.

Table 1: Demographic and socio-economic characteristics of *Brachiaria* and Napier grass farmers in Siaya an Makueni counties

Explanatory variables	Mean			t-test	
	Napier grass farmers n = 126	*Brachiaria* grass farmers n = 111	Overall	Significance (two-tailed)	χ^2-value
Socioeconomic characteristics					
Sex of household head (1 = male; 0 = female)	0.77 (0.422)	0.77 (0.42)	0.77 (0.42)		0.01
Age of household head (years)	54.2 (13.94)	58.85 (13.12)	56.38 (13.38)	2.70***	
Formal schooling of household head (years)	10.33 (8.93)	10.71 (3.62)	10.51 (6.96)	0.43	
Dairy farming experience (years)	11.04 (13.94)	12.65 (11.16)	11.79 (12.18)	1.01	
Experience in fodder production (years)	9.99 (8.83)	10.14 (10.23)	10.05 (9.49)	0.12	
Household size (count)	5.58 (2.4)	5.9 (2.91)	5.74 (2.65)	0.9337	
Main source of household income (1 = off-farm; 0 = farm)	0.66 (0.48)	0.76 (0.43)	0.70 (0.46)		2.72*
Farm characteristics					
Farm size (acres)	2.96 (2.82)	4.37 (5.22)	3.62 (4.17)	2.62***	
Land tenure[1] (1 = owned with title deed; 0 = otherwise)	0.56 (0.50)	0.69 (0.46)	0.62 (0.49)		4.78**
Tropical livestock unit (TLU)[2]	6 (4.2)	9.36 (9.20)	7.58 (7.18)	3.68***	
Breed type (1 = exotic breed; 0 = otherwise)	0.61 (0.49)	0.91 (0.29)	0.75 (0.43)		28.18***
Cash crop farming	0.37 (0.48)	0.44 (0.5)	0.4 (0.49)		1.43
Farmer's perception					
Perception of milk productivity (continuous measures as a factor score)	3.45 (0.68)	4.27 (0.55)	3.83 (0.74)		100.30***
Institutional characteristics					
Group membership (1 = yes; 0 = no)	0.6 (0.49)	0.87 (0.33)	0.73 (0.44)		21.94***
Access to credit (1 = yes; 0 = no)	0.3 (0.46)	0.4 (0.5)	0.37 (0.48)		5.60**
Access to extension (1 = yes; 0 = no)	0.60 (0.49)	0.84 (0.37)	0.63 (0.48)		47.88***
Outcome variable					
Gross margin per acre (USD)	447.42 (464.79)	989.14 (851.66)		6.15***	

Source: Survey data

Notes: 1. Land tenure refers to ownership of land (with and without title deed). 2. The tropical livestock unit (TLU) conversion factor is based on Storck and Doppler (1991): sheep and goats = 0.13, cows and oxen = 1, calves = 0.25, weaned calves = 0.34. ***, ** and * represent significance at the 1%, 5% and 10% probability levels respectively. Standard deviation in parentheses.

4.2 Determinants of *Brachiaria* grass adoption

The first stage of the endogenous switching model was a probit regression that evaluated factors that influence the adoption of *Brachiaria* grass. The results are presented in Table 2. A test of normality was run using the Jarque-Bera test (Appendix A). The study concluded that the error terms were normally distributed, given that the calculated probability of chi^2 was greater than the stated ($prob > chi^2 = 0.432$). Therefore, the probit model was fit for estimating the first step. The first two columns represent a probit model estimated independently following Equation (1), while the last two columns show the joint probit estimated using endogenous switching regression.

The coefficient for age was positive and significant, implying that older farmers are more likely to adopt *Brachiaria* than younger farmers. This concurs with previous findings by Asfaw *et al*. (2012), who suggest that experience (associated with age) increased the adoption of improved pigeon pea in Tanzania. Benefits from established fodder are not immediately clear in comparison to one-season crops such as maize, and require a longer period to realise returns from sale or improved milk production (Holmann *et al*. 2004). In terms of fodder, production enterprises reap the benefits from increased milk production or the sale of fodder. Older farmers are therefore more likely to invest in fodder and reap the benefits later compared to younger farmers. The coefficient for years of experience in fodder production was negative and significant, suggesting that farmers who have more experience in fodder production are less likely to adopt *Brachiaria*. This is likely because farmers with more experience have technical knowledge of fodder production from the alternatives, which they have obtained over years, compared to farmers who are starting with fodder production using new fodder technology.

The coefficients for indicators of farmers' wealth (herd size given by TLU and breed type) were positive and significant, implying that farmers with larger herd sizes and better breed types are more likely to adopt *Brachiaria*. The findings corroborate those of Khan *et al*. (2014), Murage *et al*. (2015a, 2015b) and Kassie *et al*. (2018), who found that ownership of dairy cattle increased the adoption of push-pull technology in that they can utilise the *Brachiaria* produced. Therefore, ownership of productive resources such as livestock creates the need for farmers to source adequate quantities of fodder, even in periods of feed scarcity.

Farmers' perceptions that *Brachiaria* increased milk productivity significantly increased the probability of adoption. The results corroborate those of Murage *et al*. (2015b), who observed that farmers adopted push-pull technology that utilises *Brachiaria* over the conventional one, which uses Napier grass, since it resulted in other benefits such as increased fodder in dry seasons and increased milk production. Murage *et al*. (2015b) noted that farmers preferred the former technology because it resulted in increased cereal production, an improvement in soil fertility and a reduction in *Striga* weed infestation. Therefore, as noted by Adesina and Zinnah (1993), the adoption of technologies is influenced by farmers' perceptions of their attributes and effectiveness.

The coefficient of group membership was positive and significant, implying that membership of a social group increases the probability of adopting *Brachiaria*. The findings are similar to those of Kassie *et al*. (2015), who found that farmers belonging to social groups were more likely to adopt sustainable intensification practices such as improved crop varieties and fertiliser. A possible explanation is that social networks facilitate the flow of information, such as on new farming opportunities and access to markets, finance and inputs. Social groups among farmers can also act as informal insurance during the crisis caused by food shortages and a lack of money for inputs and other needs (Quisumbing 2003).

Table 2: Determinants of adoption of *Brachiaria* among dairy farmers in Siaya and Makueni counties (probit model)

	Independent probit model for adoption		Joint estimated probit	
Variables	**Coef.**	**Std err**	**Coef.**	**Std err**
Constant	-7.636***	1.042	-7.321***	1.005
Socioeconomic characteristics				
Sex of household head (1 = male; 0 = female)	0.022	0.26	-0.041	0.26
Age of household head (years)	0.023**	0.01	0.020**	0.01
Years of schooling of household head (years completed)	-0.02	0.019	-0.017	0.018
Dairy farming experience (years)	0.004	0.011	0.004	0.011
Experience in fodder production	-0.032**	0.016	-0.034**	0.016
Household size (count)	0.005	0.042	-0.002	0.0421
Main source of household income (1 = off-farm; 0 = farm)	0.041	0.244	0.113	0.2462
Farm characteristics				
Farm size (acres)	-0.018	0.044	-0.006	0.046
Land tenure (1 = owned with title; 0 = otherwise)	0.086	0.242	0.042	0.242
Tropical livestock unit (TLU)	0.064***	0.024	0.065***	0.025
Breed type (1 = exotic breed; 0 = otherwise)	0.751***	0.194	0.706***	0.189
Cash crop farming	-0.116	0.232	-0.079	0.229
Farmer's perception				
Perception of milk productivity	1.036**	0.169	1.02***	0.166
Institutional characteristics				
Group membership (1 = yes; 0 = no)	0.618**	0.282	0.537**	0.269
Access to credit (1 = yes; 0 = no)	0.145	0.22	0.174	0.221
Access to extension (1 = yes; 0 = no)	0.448*	0.25	0.48**	0.245
Number of observations	237		237	

Source: Survey data
Notes: ***, ** and * represent significance at the 1%, 5% and 10% probability levels respectively.

It was observed that farmers who had access to extension services were more likely to adopt the improved fodder. As expected, contact with extension services facilitates awareness and flow of information and increases access to training on new technology and the benefits associated with it. The findings are consistent with those of Kassie *et al*. (2015), who found that access to extension services was associated with increased adoption of soil and water conservation technologies in Ethiopia, Kenya, Malawi and Tanzania.

4.3 Determinants of the magnitude of the opportunity cost of adopting *Brachiaria* grass

The results of the second-stage endogenous switching regression explaining the variation in opportunity cost (differences in the GM) are presented in Table 3.

The estimates of the coefficients of correlation between the error terms in the adoption equation and the outcome equation are given by ($\rho1$, $\rho0$) and are significant and positive only for the correlation between the adoption equation and the gross margin for the Napier equation. This implies that the gross margins for Napier grass farmers are relatively lower than those of *Brachiaria* grass farmers. Furthermore, the significance of the two equations in the model, (r1r2), suggests self-selection in the adoption of *Brachiaria*. This justifies the use of the endogenous switching model to correct self-selection. Moreover, the likelihood ratio test for selection and outcome equations is significant, implying there is dependence between the two system equations.

Table 3: Determinants of the opportunity cost of adopting *Brachiaria* in Siaya and Makueni counties

Variables	*Brachiaria* grass farmers		Napier grass farmers	
	Coefficient	**Std error**	**Coefficient**	**Std error**
Constant	9.3492***	1.143	8.359***	0.506
Socioeconomic characteristics				
Sex of household head (1 = male; 0 = female)	0.402	0.265	0.149	0.2
Age of household head (years)	-0.002	0.012	0.001	0.007
Years of schooling of household head (years completed)	0.03	0.031	0.005	
Dairy farming experience (years)	0.002	0.015	0.005	0.009
Experience in fodder production	0.006	0.017	0.005	0.014
Household size (count)	-0.024	0.036	-0.062*	0.035
Main source of household income (1 = off-farm; 0 = farm)	-0.052	0.261	0.488***	0.182
Farm characteristics				
Farm size (acres)	0.122***	0.027	0.074**	0..035
Land tenure (1 = owned with and without title; 0 = leased in)	0.464*	0.256	-0.355**	0.183
TLU	-0.017	0.015	0.042*	0.025
Breed type (1 = exotic breed; 0 = otherwise)	0.041	0.204	0.437***	0.15
Cash crop farming	-0.065	0.212	-0.194	0.204
Institutional characteristics				
Access to credit (1 = yes; 0 = no)	0.121	0.209	-0.052	0.184
Access to extension (1 = yes; 0 = no)	-0.119	0.324	-0.057	0.197
r1r2	-0.282	0.315	0.629**	0.271
$\rho_1\rho_0$	-0.275	0.291	0.558**	0.187
LR test for joint independence		5.81**		
Log-likelihood		-414.568		
Number of observations		237		

Source: Survey data

Notes: ***, ** and * represent significance at the 1%, 5% and 10% probability levels respectively; r1r2: Transformation of the correlation of the error terms in the fodder choice equation and outcome equation; ρ1ρ0: Correlation coefficient between error terms of the system equations

The results indicate that the opportunity cost of growing Napier rather than *Brachiaria* increases with tenure security of the land. Farmers who own land with a title deed earned less gross margins from Napier compared to farmers who grow it on leased land. This is probably because those farming leased land have the incentive to use more inputs and make profit on fodder relative to those who own their land. In contrast, the opportunity cost of growing Napier reduces with land size because farmers with more land for fodder production tended to have higher gross margins.

Similarly, ownership of productive resources such as larger herd size and better breed types reduced the opportunity cost of growing Napier grass. This is because such resources make it possible for farmers to invest and get higher gross margins on Napier. The results further indicate that the more sources of off-farm income, the higher the gross margins from Napier and therefore the lower the opportunity cost. A likely explanation is that such farmers can buy inputs such as fertiliser to increase the yields and profit from Napier. A comparable effect of off-farm income was recorded by Mutoko *et al*. (2015), who found that farmers earning off-farm income hired labour, which explains their higher allocative efficiency in maize production. Furthermore, farmers with access to off-farm income are likely to buy and apply farm inputs at the appropriate time, generating higher output and gross margins from Napier grass.

The larger the household size – the proxy for family labour, the higher the opportunity cost of growing Napier grass. This is probably because the unpaid family members provide labour beyond the optimal quantity, resulting in diminishing returns per labour input. Therefore, the gross margins from Napier grass are much lower compared to those from *Brachiaria*. This is consistent with the findings of Mutoko *et al*. (2015), who found that household size reduces the technical efficiency of farmers in producing maize.

4.4 Average effect of adopting *Brachiaria* grass

Table 4 presents the average gross margins for *Brachiaria* and Napier grass. To determine if the opportunity cost of *Brachiaria* is greater or smaller for adopters had they not adopted or non-adopters had they adopted, the transitional heterogeneity effects were computed by taking the difference in opportunity for *Brachiaria* and Napier grass (ATT and ATU).

Table 4: The opportunity cost of growing *Brachiaria* grass

	Napier grass (opportunity cost)	*Brachiaria* grass (opportunity cost)	Transitional heterogeneity (ATT - ATU)
Annual gross margin per acre (USD[5])	578.25 (578.25)***	657.99 (243.93)***	79.74

Source: Survey data
*** represents significance at the 1% level. The figures in parentheses are standard deviations; ATT: Treatment effects on the treated; ATU: Treatment effects on the untreated

The transitional heterogeneity (TH) is positive (USD 79.74), implying that there are systematic differences among the farmers. Farmers who adopted *Brachiaria* grass had higher gross margins and therefore lower opportunity costs than Napier grass farmers. Therefore, Napier grass farmers would be worse off compared to *Brachiaria* farmers if they were to consider fodder production as a business.

5. Conclusions and policy implications

The results from the study show that the adoption of *Brachiaria* grass is significantly and positively influenced by age, asset endowment (given by herd size, type of breed), group membership, access to extension, and farmers' perceptions of milk production. Farmers who opt not to adopt *Brachiaria* in favour of Napier grass face a high opportunity cost. Furthermore, the magnitude of the opportunity cost increases with tenure security (ownership of land with title deed). Household size and asset endowment (farm size, breed type, herd size, and off-farm income) reduce the magnitude of the opportunity cost of growing *Brachiaria*. The results of the study indicate that farmers stand to benefit more financially from *Brachiaria* compared to Napier, suggesting that there is a need to expose more farmers to the technology. Efforts are therefore needed to strengthen extension services and existing rural collective action institutions to increase awareness and promote improved fodder technology. There is a need for an effective, multi-stakeholder partnership to promote the dissemination of knowledge of *Brachiaria* among farmers. Similarly, further research should also focus on improving farmers' access to fodder markets, given the potential financial returns from *Brachiaria* grass production.

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[5] At the time of analysis (2018), $1 = 100.3 Kenya shillings

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Appendix A: Test of normality

Skewness-Kurtosis test (Jarque-Bera)
Ho: Normal distribution Chi^2 (2) = 1.558 Prob > Chi^2 = 0.432

The study failed to reject the null hypothesis and concluded that the error terms are normally distributed.