Risk and Social Interactions in the Adoption of Improved Dairy Breeds by Smallholder Farmers in Kenya

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Abstract

This study investigates the role of production risk and social interaction in the adoption of improved dairy breeds by smallholder farmers in Kenya.

In agricultural production outputs are uncertain and they may turn out to be favorable or unfavorable. Therefore, farmers may not always get the output they expect to produce. Deviation from expected output constitutes production risk. This form of risk is said to hinder the adoption of yield increasing technologies. Farmers rarely have complete information about the performance of new agricultural technologies. Lack of perfect information about the performance of new technologies may as well hinder adoption. To fill the information gap farmers seek to acquire information through formal and informal sources. Informal sources include social interations with peers and neighbors.

Flexible moments method is used to derive production risk variables. The mean values of selected variables of a reference group defined at village level are used as proxies for social interactions. The study applies three different methods, probit, two-stage instrumental variable, and control function on cross-sectional data collected from a sample of 373 smallholder farmers to evaluate role of risk and social interactions in the adoption of improved dairy breeds.

The finding shows that endogenous social interactions as measured by proportion of improved breeds' adopters in a reference group have positive and significant effect on adoption of improved dairy breeds. Production risk as measured by variance and skewness of milk output is found to have negative and significant effects of adoption of improved dairy breeds.

Keywords: Production risk, social interactions, technology adoption

Introduction

Agricultural technologies with high productivity potential still face the challenges of low adoption (Duflo, Kremer & Robinson, 2011). Investing in yield increasing technologies is risky, since agricultural production takes place in environment characterized by unfavorable weather conditions, pests, diseases, and price fluctuations (Harvey et al, 2014). Farmers often do not have perfect information about the outcomes of production choices which may turn out to be favorable or unfavorable (Gaurav & Mishra, 2012).

Yield increasing agricultural technologies are associated with higher risks and risk-averse farmers tend to avoid (Brick, Visser & Burns, 2012). Uncertainties in the expected output may influence production decision. Farmers rarely have complete information about the performance of new agricultural technologies (BenYishay & Mobarak, 2014). To fill the information gaps, farmers search for information from extension agents among other sources such as peers and neighbours within their social networks (Foster & Rosenzweig, 2010; Conley & Udry, 2010). Agricultural production decisions are said to be shaped within social contexts (Gaurav and Mishra, 2012).

Risk consinderation may hinder adoption of yield increasing technologies (Kassie et al., 2009; Ogada et al., 2014). Technology uptake may depend on the extent to which a farmer can cope with risk hence risk-averse farmers avoid yield increasing technologies due to associated risk (Simtowe, 2006). Production decisions may be influenced by social interations (Munshi, 2004; Baindera & Rasul, 2006; Gathiaka, 2012) since farmers observe and learn from each other. It seems that risk and social interactions play a role in agricultural decision making. However , there is scanty literature where these two aspects are studied together (Yu et al., 2014).

Smallholder dairy farming in Kenya is characterized by low productivity. In the Central and Rift valley regions of the country, ecological conditions are conducive to dairying but milk production from these regions is low. The yield per cow averages 2 to 4 litres per day compared to 20 litres that is achievable in some farms within the region (Karanja, 2003). This level of productivity is much lower than in the developed countries (Majiwa et al., 2013). Low production in the dairy sector can be attributed to low adoption of improved dairy breeds (Baltenweck & Staal, 2000). To boost the uptake of agricultural technologies, it is important to understand and address the drivers of adoption (Barham et al., 2004). These drivers are not always obvious or well known.

Drawing from (Kassie et al., 2009; Ogada et al., 2014) and (Bandiera & Rasul, 2006; Foster & Rosenzweig, 2010; Gathiaka, 2012) respectively, risk and social interactions influence adoption of agricultural technologies. However, the combined effect of these two aspects is least studied in the literature of technology adoption. This paper shed more light on the influences of risk and social interations in the adoption of improved dairy breeds by smallholder farmers in Kenya.

Risk in technology adoption

In agriculture risk arises due to uncertainty over factors that determine returns in production (Koundouri et al., 2006). Risk is often associated with potential negative outcomes which negatively alter farmer's well-being due to likelihood of loss of output. Risk consideration influences production decision in terms of input choice and technology adoption (Simtowe, 2006; Kassie et al., 2009). Exposure to risk hinders technology adoption (Rosenzweig & Binswanger, 1992). Farmers strive to prevent or reduce risk (Bocque'ho et al., 2010). Farmers are vulnerable[1] and likelihood that a risk may result to loss of welfare makes them avoid risky technology. A farmer may forego a potentially high yielding technology due to risk (Carter et al., 2016). Yield and risk are to some extent inversely correlated, a technology that is potentially very productive is perceived to be more risky. One measure of risk is the gap between potential and actual yields. The higher the yield potential, the wider is the yield gap and high risk in case of failure (Chapagain & Good, 2015). A farmer will hesitate to adopt a technology if the expected return is lower than the costs. Low production due to risk-aversion may create a poverty trap[2] and risk is said to contribute to the worsening social welfare in the absence of mechanisms that serve to minimize its effects (Dercon et al., 2007). Technology avoidance as a risk mitigation strategy may reduce household welfare and result in poverty (Kassie et al 2009). In the absence of insurance, risk is a major concern in adoption of a new technology (Brick et al., 2012). Faced with uncertainty, resource- constrained households may opt for less risky technologies and fail to undertake activities that have higher expected outcomes because of associated risks (Menapace et al., 2012).

Attitudes towards risk are in three categories- risk averse, risk neutral and risk lovers. Risk averse farmers tend to choose low risk even though low-yielding technologies. Risk takers adopt new technologies without much consinderation to risk. Maximizing expected utility is a common concept in decision making under risk. Given a set of production alternatives, a farmer will choose the alternative with the highest expected utility. Expected utility is maximized when variance of expected output is minimal (Koundouri et al.,

[1] Maunder and Wiggins (2006) points out that majority smallholder farmers live close to the edge and relatively minor shocks, such as erratic rainfall in a season, can be enough to trigger poverty.

2 Dercon points out that, "If the high return activity is also more risky, then differences in risk aversion may explain differences in portfolios across households. Poor households may then stay poor in the long run because they are risk averse".

2006). Therefore, the technology adopted by a farmer is not necessarily the one with maximum net returns. Profitability of an agricultural technology is a necessary but not sufficient condition for it adoption. The greater the benefit associated with a technology the more the acceptable risk, hence a trade-off between benefits and risks (Hansson et al., 2014). Farmer's decision are shaped by the tradeoff between benefits and risks, hence risk averse farmers seek technology with attributes that increase productivity or decrease risk.

Social interactions in technology adoption

Informated farmers can make better choices in relation to inputs and technologies choice. Unfortunately, farmers operate with incomplete information about production and markets (Fafchamps & Minten, 2012). A farmer may opt for a technology that he has better information about even if it is less productive compared to a new technology which he has little information about (Foster & Rosenzweig , 2010). Agricultural extension is a major source of information but it is weak in many developing countries (Anderson & Feder 2007). Other sources of agricultural information and knowledge include informal channels such as social networks of neighbors and peers (Mekonnen et al., 2016). Social interactions become important in shaping production decisions in smallholder agriculture in the absence of extension services (Davis & Place, 2003). Foster and Rosenzweig, (1995) points out that the decision to adopt a technology by a farmer is positively influenced by prior[3] adoption of the technology by those other farmers that the reference farmer interacts with. Therefore, not only market but non-market factors that influence farmers choices. An agent may derive utility from social acceptance and therefore make decision contingent on other agents' acceptance (Moser & Barrett, 2006). Economic actions of decision makers are said to be embedded in the structure of social relations (Munshi, 2004). Information gathered from a social network may affect a farmer's perception of the relative advantage of a new technology (Munshi, 2004). A social network may be a village, a group of friends or associates and is defined within a geographical or associational proximity. Social networks at times help to build social capital[4] which refers to features such as trust, norms and collective value. Within a social network there are social interactions which occur when a member in a network influence another member's decision. Social interactions are non-market and cannot be determined by the price mechanism. For this reason, social interactions are sometimes called non-market interactions. They are determined by actions and characteristics of interacting agents within networks.According to Manski (1993), there are

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3 Adoption is a function of own and neighbors' past stock of adoption (Rogers, 1995)

4 Social capital defines quantity and quality of social relationships

three reasons why the interactions influence behavior. First, agents in the same group tend to behave in the same way because of similar environments. They may also have similar characteristics that lead them to self-select into a given social network. This is referred as correlated effect. Agents also tend to behave as others in a social network because of similar background characteristics. This is referred as contextual effect. Finally, agents tend to uptake something given its prevalence within a social network. This is referred to as endogenous effect. Endogenous effect may be due to pure imitation, leveraging on the most common, or due to informational conformity[5]. Social interactions may result in increased production; say increased use of an input by a farmer after observing the other farmers in a network. This is an outcome of social learning as (Duflo et al., 2011; Gathiaka, 2012) point out.

Lack of reliable information about a new technology is a likely barrier to its adoption (Bandiera & Rasul, 2006). Information helps to reduce the perceived risk and uncertainty associated with a particular technology. Golman et al., (2015) define uncertainty as lack of perfect information and risk as exposure to unfavorable consequences. Social interactions are an important way reducing information asymmetry (Conley & Udry 2010). Initial adoption of new technology may be low but with time and more information adoption is accelerated (Maertens, 2012). Social interactions trigger feedback of actions among interacting parties. As the number of adopters in a network increases, the likelihood of more adopters outside the network also increases (Bandiera & Rasul, 2006). Social relations enhance development of knowledge through exposure to new ideas and information.

Materials and Methods

Data and study area

The data for this study were collected in Ol'kalou area of Nyandarua County and Kabiyet, Siongiroi and Metikei regions of the Rift valley. These regions are considered high potential area for milk production. Nyandarua County has an elevation of 2400-3000m and rainfall of 1150-1600mm. The area is predominantly agricultural where mixed farming is mainly practiced. Kabiyet, Siongiroi and Metikei regions have an elevation that range from 1600-2800m and rainfall of 1150-1650mm.

To compute a representative sample daily milk production was chosen as the appropriate variable to use in the calculation of a representative sample. The sample size was obtained by applying the formula (equation 1).

[5]Assumption is that what is used by many is much better.

$$N = \left[\frac{(Z_{\alpha} + Z_{\beta})\sigma}{\delta} \right]^2 \quad \textbf{(1)}$$

Where Zα is the standard normal value representing the significance level for a 1-sided test (5%), δ is the difference to be identified, σ is the standard deviation of the difference and Zβ is the standard normal value representing the power to detect this difference as being significant at 80% (Woodward, 2013). According to a previous study, in the context of a small holder dairy development, it was taken that an increase of 1.25 liters of milk per day would be significant base on median yield of 2 to 4 liters per day for smallholders' farmers in Kenya and the standard deviation of milk production per cow was 4.3 (Staal et al., 2001). The same estimates were used to calculate required sample per site. Applying the formula in (equation 1) a minimum sample of 73 households per site was required and in total sample of 373 for the four sites was obtained.

Descriptive statistics

Table 1: Summary Statistics of Variables used in the Analysis

	Total sample		**Adopters**		**Non-Adopters**	
Variables	**Mean**	**Std Dev**	**Mean**	**Std Dev**	**Mean**	**Std Dev**
Household Head age	48.55	13.96	48.99	13.69	47.3	14.71
Household Head gender	0.83	0.38	0.82	0.38	0.85	0.35
Head farming experience	20.81	13.59	21.49	13.69	18.84	13.15
Head years of schooling	7.96	4.49	8.4	4.59	6.7	3.94
Household income (000/yr)	174.63	162.29	200.36	169.54	100.43	128.68
Ave years of farming /village	20.81	3.12	21.18	3.29	19.76	2.3
Ave years of schooling/village	7.96	1.08	8.18	1.1	7.31	0.74
Average income/hub (000/yr)	111.9	41.7	121.4	40.72	84.88	31.31
Proportion of adopters/village	0.74	0.24	0.81	0.21	0.53	0.15
Output Variance	0.84	0.11	0.83	0.1	0.87	0.11
Downside risk	0.32	0.3	0.33	0.29	0.27	0.3
Total acres of land	11.92	33.82	11.63	24.22	12.75	52.67
Experience Fodder shortage	0.78	0.41	0.76	0.43	0.84	0.36
Practice fodder conservation	0.26	0.44	0.31	0.46	0.11	0.32
Practice land conservation	0.57	0.5	0.59	0.49	0.5	0.5
Sold cow within the year	0.4	0.49	0.45	0.5	0.25	0.44
Access to credit	0.08	0.27	0.09	0.29	0.04	0.2
Trained in Business	0.25	0.43	0.26	0.44	0.23	0.42
Number of extension visits	3.71	2.38	3.86	2.16	3.27	2.91
Distance to market	0.54	1.08	0.31	0.62	1.22	1.68
Sample size Adopters 277 , Non Adopter 96= Total 373						

Derivation of production risk variables

In dairy production, a farmer utilizes a vector of inputs X, (land, labor, and feed) to produce an output *q* of milk. Production is a stochastic function affected by random factors that cause variability in output. In a stochastic production function, the variability in yield represents risk.

Assuming the production technology q= f(X), modifying the production function as in (Koundouri et al., 2006), milk output (q) can be estimated by the function.

$$q = f(b(\lambda), X) + e \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

where b is breed type, λ is farmer characteristics, X is a vector of inputs used in milk production, and e is a random variable which summarizes omitted variables, unobserved variation in output and production shocks.

Assume further that yield variability is the only source of uncertainty. The variability could emanate from weather changes,or disease outbreak. The profits of dairy production can be respresneted as.

$$\pi = pq\text{-}c \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. (3)$$

where π is profit, q is milk output, p is milk price and c is total cost of production. Whenever there are negative shocks that cause yields to go down, realized profits fall below expected profits, i.e., $\pi < E\pi$ where E is an expectation operator. A farmer tries to maximize expected profits. Following (Koundouri et al ., 2006) the maximization problem is as shown (equation 4).

$$\max_{X,} E[U(\pi)] = \max_{X,} \int \{U[pf(b,(\lambda),X) - r'X]\}\ dG(\varepsilon) \ldots\ldots\ldots (4)$$

Utility from profit is nonlinear and it varies depending on risk preference. For risk-averse farmers utility decreases with profit/income while for risk lovers the vice versa holds. To increase profit while holding market prices constant output must increase. Output is stochastic and subject to risk. If a high yielding technology is risky, only a risk loving farmer will adopt it. A risk-loving farmer may bear the risk in order to increase profit/income and utility. Following Pratt, (1964) the cost of risk bearing can be represented as follows:

$$EU(\pi) = U[E(\pi) - R] \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

R is the risk premium which is the difference between expected profit/income and the certainty equivalent income (CE) .

$$[E(\pi) - CE] = R \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (6)$$

In the absence of risk expected income is equal to the certainty equivalent income. The risk premium is the cost a farmer would be willing to pay to eliminate exposure to risk. Without risk the random output equates the expected output. The expected output is the mean output. If R> 0 a farmer is considered to be risk-averse, if R=0 the farmer is risk neutral, and if R<0 the farmer is risk loving.

Using Taylor's expansion series the risk premium can be calculated as follows (Di Falco et al., 2009).

$$\dot{R} = \frac{1}{2} r_a M_2 - \frac{1}{6} r_b M_3 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (7)$$

Where $M_i = E(\pi - E(\pi))^i$ for i = (1, 2,3…)

and $r_a = -\frac{\left(\frac{\delta^2 u}{\delta \pi^2}\right)}{\frac{\delta u}{\delta \pi}}$ $r_b = -\frac{\left(\frac{\delta^3 u}{\delta \pi^3}\right)}{\frac{\delta u}{\delta \pi}}$

r_a is the coefficient of Arrow-Pratt[6] absolute risk aversion while r_b measures downside risk aversion or the positive variation in output (Simtowe, 2006).

Derivation of social interations variables

Social interactions occur when preferences of a farmer are influenced by choices of other farmers in a network. Social interactions tigger "choice influence" through the tendency to act in accordance with the choices of those others that an agent interacts with. Manski (1993) demonstrates that the mean outcome of a reference group impact individual outcome within the reference group. The linear-in-means model as used by Blume et al, (2015) and Gathiaka, (2012) illustrates how reference group averages influence individual's decision. The influence of social interactions can be constructed based on a reference group such as a village or group.

$$\overline{X}_{g\,(-i)} = \sum_{1}^{n-1} \frac{X_g}{n-i} \text{..........................} \ (8)$$

Social interaction variables form ith farmer computed (equation). Where X is variable of interest, n is number of farmers in the reference group and g is the reference group.

Theoretical model

A farmer technology adoption behavior can also be explained by maximization of expected utility. A farmer will adopt new technology if the expected utility from the new technology exceeds the utility without the technology. Let U $(\pi)_{i1}$ represent the expected utility that ith farmer would receive from adopting a new technology, and U $(\pi)_{i0}$ the expected utility without the technology. The farmer will adopt the new technology if $U_{i1} > U_{i0}$ (Feder et al., 1985).

Let the perceived benefits associated with adoption (T^*) be a linear function of a vector of variables (X^1) and a normally distributed stochastic error term, ε. Then,

$$T^* = X^I\beta + \varepsilon \ \text{...} \ (9)$$

β is a vector of parameters to be estimated. A farmer adopts a new technology if:

$$T_i^* = E[U(\pi^1)] \text{-} E[U(\pi^0)] > 0 \ \text{..} \ (10)$$

where π^1 is the benefits of adopting the technology and π^0 is the benefits of non-adoption

[6] As per Arrow- Pratt, risk aversion is expressed as the 2nd derivative of utility function with respect to profit (0 <U'') while intensity (absolute risk aversion) is measured by (– U''/U').

Adoption, T= 1 if T^*> 0 (positive benefits of adoption)
Adoption, T= 0 if otherwise.

T^* can be transformed into a predicted value of probability of adoption.

Pr (T=1|X) = Pr (T^*> 0)= Pr($X^I\beta + \varepsilon$>0)= Pr ($-\varepsilon < X^I\beta$)…................(11)

This is a binary probit model of technology choice with the assumption that the disturbance term is normally distributed (Maddala, 1986). Equation (11) can be used to predict the probability whether a household will adopt a technology given a vector of explanatory variables.

Empirical model

A binary choice linear-in-means model as in (Blume et al., 2015) can be used to estimate adoption of improved dairy breeds in the light of risk and social interactions.

$$\mathrm{T_{gi}} = \beta\mathrm{X_i} + \delta\bar{T}_{\mathrm{g(-i)}} + \alpha\bar{X}_{\mathrm{g\,(-i)}} + \ \omega\mathrm{R_i}\ + v_{ig} > 0 \text{ .... (12)}$$

$\mathrm{T_{ig}}$ is the probability that farmer i in group $\mathrm{g_i}$ (i= 1,2…) adopts an improved breed;

$\mathrm{X_i}$ = Vector of explanatory variables (household characteristics-age, gender, years of schooling, farming experience, income, land size, farm assets.

Other binary variables such as fodder shortage,fodder conservation, selling cows, access to loan. The price of a grade cow

$\bar{T}_{\mathrm{g\,(-i)}}$ = Proportion of adaptors in the reference group g excluding farmer i;

$\bar{X}_{\mathrm{g\,(-i)}}$ represents averages of variables of interest in the group excluding the observation farmer (include village level averages of farming experience, years of schooling, and incomeof group members excluding the observation farmer)

R is a risk vector which contains 2nd and 3rd moment of milk output and v_{ig} is the error term, while β , δ, $\alpha$and ω are parameters to be estimated.

The probability of a farmer adopting a new dairy breed is given as:

$$\Pr([T_i = 1] = \quad \Pr([T_{0i} < T_{1i}] = \Pr\left[-Vig < \beta\mathrm{X_i} + \delta\bar{T}_{\mathrm{g(-i)}} + \alpha\bar{X}_{\mathrm{g\,(-i)}} + \omega\mathrm{R_i}\ \right] \text{.. (13)}$$

Equation (13) is estimated using maximum likelihood (MLE) method.

Estimation issues

Obtaining consistent estimates is challenged by endogeneity. Failure to control for endogeneity results in biased estimates of the effect of explanatory variables on adoption. Endogeneity may arise due correlation between the error term and some explanatory variables. Animal care visit is a choice variable since the farmer decide whether to seek prevention, curative services as well as advisory services. Therefore, farm health care visits (preventative, curative and advisory) are potentially endogenous. There are several methods that can be used to address the problem of endogenity. Most methods are anchored on instrumental variable approach. This is a variable that is correlated with the endogenous explanatory variable but not correlated with the outcome variable. The procedure is first to have endogenous variable regressed on all variables in the structural equation in addition to the instrument. From the first regression predicted value of the endogenous variable can be obtained and be used in the second regression with the outcome variable this approach is known as two stages least square instrumental variable approach. Another approach is to use residues obtained in the first regression as a variable in the outcome equation this approach is known control function. In this study result of three approaches (ordinary probit, two-stage IV and Control function) were compared. Distance to the nearest market was used as an instrumental variable for number of animal care visits. Necessary test to confirm distance to the market as a valid instrument was performed to confirm the validity of the instrument.

Results and Discussion

Determinats of adoption of Improved Breeds

Three models were used in the estimation of determinants of technology adoption, the dependent variable improved breeds is in binary (1 for adoption and 0 otherwise). Adoption is a binary outcome with likely endogenous regressors. In the case of this study farm advisory visits is potentially endogenous. Since, such visits play a major role in influencing adoption of agricultural technologies. Farm visits is likely to be endogenous where a farmer decides whether or not to seek advisory sevices. In the first stage regression the number of farm visits were used as the dependent variable and the distance to the market was used as the instrument.The validity of instrumental variable used in the first stage equation need to be tested. Test for weak instruments is based on the null hypothesis that instruments are weak. The F-statistics is for the joint significance of instruments, results found it to be 4.60 with a p-value of 0.00, this implies that instrument have significant explanatory power for endogenous regressor after controlling for the effect other independent variables. The high F-values (>10) indicate that instruments are not weak. Nominal 5% Wald test also confirms stronger instrument, since the test statistic 4.60 is less than critical value of 16.38 at 10%. Therefore, it can be concluded that the selected instrument is strong. To confirm the validity of the over identifying restrictions in the model, Sargan chi-square statistic and Basmann Chi-square statistic are used. The result shows a p-value of 30.19 and 31.27 respectively and is significant at the 10% test level, which means the instrument is valid.

Significance of the coefficient of the residual is a test for the exogeneity of the potentially endogenous variable (Hausman, 1978). The result shows significant parameter estimate of the residual, indicating the farm advisory visits is endogenous. Hence, endogeneity is a problem and probit estimate would yield biased estimate if endogeneity is not controlled. Including residues obtained from the first equation together with other regressors help in controlling endogenity in the second equation estimation. The results are as shown in (Table 2).

Table 2: Determinants of improved breeds adoption

	Probit	IV_2sls	Control Function	M/effects (CF)
House head characteristics				
Household Head age	-0.002(0.01)	0.016(0.01)	0.014(0.01)	0.003
Household Head gender(male)	-0.210(0.28)	-0.135(0.28)	-0.136(0.28)	-0.025
Head farming experience	0.02(0.01)	-0.03(0.01)	-0.001(0.01)	-0.001
Head years of schooling	0.02(0.02)	-0.012(0.03)	-0.013(0.03)	-0.0025
Households income	0.01(0.01)	0.01(0.00)	0.001(0.00)	0.001
Land size (acres)	-0.010(0.00)	-0.008(0.00)	-0.011(0.00)	-0.002
Farm assets ownership	0.43(0.28)	0.220(0.29)	0.253(0.29)	0.047
Contextual social effects				
Avg hhead years of farming experience /village	-0.052(0.07)	-0.04(0.06)	-0.07(0.07)	-0.014
Avg household years of schooling/village	-0.24(0.31)	-0.89**(0.4)	-0.933**(0.43)	0.181
Average income/village	.03(0.01)	0.01*(0.01)	0.012*(0.001)	0.0022
Endogenous social effects social				
Proportion of adopters/village	4.5***(1.5)	5.7***(1.6)	6.2***(1.66)	1.19
Risk measures				
Expected milk output (mean)	0.88***(0.2)	.65***(0.2)	0.711***(0.20)	0.138
Output variance(2nd moment)	-0.29***(0.2)	.25**(0.15)	-0.282**(0.15)	0.054
Output skewness (3rd moment)	-0.23***(0.1)	-0.15**(0.1)	-0.18**(0.08)	0.035
Proxies (other agricultural activities))				
Experience Fodder shortage	-0.15(0.23)	-0.19(0.24)	-0.160(0.24)	-0.029
Practice fodder conservation	0.35(0.27)	0.398(0.27)	0.386(0.27)	0.067
Practice land conservation	0.22(0.21)	0.019(0.23)	0.025(0.23)	0.004
Sold cow within the year	0.33(0.21)	0.57**(0.2)	0.579**(0.24)	0.105
Obtained a loan	0.23(0.45)	0.385(0.47)	0.387(0.47)	0.061
Price of a grade cow	0.03(0.01)	0.009(0.02)	0.011(0.02)	0.002
Endogenous variable				
Farm visits(animal health care and advisory)	.174***(0.05)	.82***(0.3)	0.787***(0.27)	0.153
Residue term of animal health care visits			-0.65**(0.27)	
Constant	-0.537(2.73)	0.851(2.74)	1.541(2.89)	

Notes: *Significant at 10% level**Significant at 5% level; ***Significant at 1% level.

Household characteristics

Household characteristics were found to have mixed effects on adoption of improved breeds although not in a significant way. For instance, age, income and ownership of farm assets have a positive effect while gender, farming experience, years of schooling, and land size had a negative effect on adoption of improved breeds. After controlling for endogeneity age is found to have positive effects on adoption of improved breeds. The expected effect of age on technologies adoption depends on several factors. When age is used as a proxy for experience; it may imply that older farmers are more experienced and more likely to make informed farming decisions, therefore a positive effect on adoption. If age is assumed to proxy behavior, older farmers are assumed to have shorter planning horizon and are more risk averse than younger farmers. Previous studies found the effect of age of technology adoption to be indeterminate since they can influence adoption either way. There is contention on the effect of age on adoption. Kaaya et al.,(2005) found age of a farmer to have a positive relation on adoption of artificial insemination (AI) services by Ugandan dairy farmers, while (Kassie et al., 2009) found age to have negative effects on adoption of agricultural technologies. Gender has insignificant and negative effect on the adoption of improved breeds. The insignificant influence of gender is in line with (Peterman et al., 2014) who found that male and female farmers behave the same when it comes to adoption decisions making. The effect of gender of technology adoption is expected vary with the technology type and the question of whether the agricultural technology is gender neutral or not is yet to be answered since some study finds positive effects while others found negative effect. Generally though, years of schooling is expected to have positive influence on technology adoption. Mwabu et al., (2006), found education to be positively associated with adoption of new maize varieties in Kenya. Khanal and Gillespie, (2013) found that younger and more educated farmers are more likely to adopt advanced breeding technologies. The education level is considered to be complementary to the access to information and education enhances ability to understand and assimilate information about technologies. Household head income is found to have positive effect on adoption of improved dairy breeds, although insignificant. On and off-farm income are said to be an important factor for overcoming credit constraints faced by the rural households in many developing countries. Incomes provide farmers with purchasing power for productive technologies (Fernandez-Cornejo et al., 2007). Land size is found to have negative and insignificant effect on adoption of improved breeds. This result may not be surprising in the context of improved dairy breeds where farmers with small farmers prefer dairy intensification. The positive effect of farm asset ownership on improved breeds adoption is as per expectation since assets ownership may signify wealth, implying potential to afford new technologies.

Contextual Social interactions

Exogenous effects are grounded on the argument that propensity for a given type of behavior varies with the background characteristics of the agents in a reference group (Manski, 1993). These effects are captured by the mean of directly relevant variables within agent *i* reference group.

Average village farming experience has negative but insignificant effect on adoption of improved breeds. The negative effect of village level farming experience is contrary to expectation in the sense that increase in average farming experience for a reference group may imply accumulation of knowledge that influence adoption. However, it may be argued that it is experience of specific that matter but not agricultural experience in general.

Negative and significant influence on adoption of improved breeds is also observed for average years of schooling at the village level. This could be related to off-farm effect related to education, where educated people seek for employment as opposed to farm income. Other studies however, (Wydick al at., 2011) found that an increase average education at reference village increase likelihood of credit uptake from microfinance institution.

Effect of average income is found to positively and significantly influence adoption of improved dairy breeds. Margin effects show that a unit increases in income increases the likelihood of adoption by 0.22 per cent. The positive effect of average income for the reference group is not surprising in the sense that rich farmers may bring benefit to other farmers in their village which may influence uptake of technologies.

Endogenous Social Interactions

The result shows that proportion of adopters in the reference group has a positive and significant effect on adoption of improved breeds. The propensity of adopting a technology is said to literally vary with prevalence of that technology in a particular reference group. The rationale of endogenous social effects is on the basis that the agents in the reference group who have adopted will raise the i^{th} agent marginal benefits of adopting technology. The results from this study confirmed this proposition. The endogenous effects as proxied by proportion of improved breed adopters less the i^{th} agent was found to be positive and significant at 1 per cent. Basically agents in a reference group imitate each other; this imitation could be for various reasons such as pure conformity to fit with peers, informational conformity for observed peers seems to be better off with it. Wydick et al., (2011) found evidence of endogenous effects in rural Guatemala, the study found that access to credit through micro finance, banks or informal sector to be positively influenced by the proportion of credit holders in the reference group as was defined by church membership. Banderia and Rusal, (2006) also found a positive endogenous effect in sunflower technology adoption in rural Mozambique where adoption was positively influenced by proportion of adopters in the reference group.

Production risk

Risk as measured by variance and skewness of milk output is found to have negative and significant effects of adoption of improved dairy breeds. An increase in output variance[7] decreases the likelihood of improved breed adoption by 5.4 per cent. This result is consistent to previous studies. Ogada et al., (2010) found a negative effect on 2nd moment on adoption of fertilizer by farmers in Kenya. Koundouri et al.,(2006) found a negative effect on adoption of water technologies in Greece. Kassie et al., (2009), found the same result on adoption of conservation technologies in Ethiopia. Milk yield variability creates uncertainty in production and such variability may negatively affect technology adoption of improved breeds'.

The third moments represent possibility of production failure; the results revealed a negative effect on adoption implying that likelihood of production failure significantly decreases the probability of adopting improved breeds. Marginal effects shows that a unit increases of 3rd moment decrease the likelihood of improved breed adoption by 3.5 per cent. Studies such as (Ogada et al., 2010; Kassie et al., 2009) found a negative effect on 3nd moment on adoption of agricultural technologies. Farmers perceive improved breeds to be delicate hence high likelihood of production failure. The implication is that yield increasing technology may be attractive but the possibility of production failure may inhibit adoption. The result found that means output have positive and significant effect of adoption of improve breed. Marginal effects shows that a unit increases in mean output increases likelihood of adoption by 13.8 per cent. Kassie et al., (2009) also found a positive mean effect on adoption of fertilizer by Ethiopian farmers.

[7] Signifying high level of risk

Other related agricultural technologies

Within the context of specific technology, other agricultural technologies may contain useful information when interpreted within the framework farmer decision making. The proxies used in the specific model of determinants of adoption of improved dairy breeds represent some expectations with respect to is adoption.

Fodder shortage is found to have a negative effect but insignificant effect on improved dairy breed adoption. This may be a signal that fodder shortage hinder adoption of improved and this make sense in that improved breeds require high quantity of feeding and in absence of such feed farmers may opt for local breeds. On the other hand this study found a positive effect of fodder conservation on improved breed adoption, the rationale could be that farmer who conserve feed are well prepared and they have no worry for feeding improved breeds even it times of shortage-fodder conservation can be considered as a risk mitigation strategy. A farmer practicing fodder conservation is more likely to adopt improved breeds by 6.7%. The result shows a positive and significant effect of cattle trading on adoption of improved dairy breeds. This may be explained by the fact that farmer consider cows as assets and the great value they attach to then the higher the likelihood of acquiring them Marginal effects show that cattle trades have 10.5% higher likelihood of adopting improved breeds.

The result of this study indicates that access to dairying loans (access to credit) has a positive effect on the adoption of improved breeds. The results confirm that the lack of credit is a barrier to adoption as found out in various studies. Farmers need physical and financial access of technologies and the lack of credit inhibits adoption. Baltenweck and Staal, (2000) found that access to credit facilitated adoption of improved cattle breeds in Kenya, the study further argued that lack of credit is a strong reason for delaying adoption of grade cows.

The price of an improved dairy breed is found to have positive effect on adoption of improved dairy breeds, implying that if the technology have a high value then likelihood of adoption it is also high. This conforms to other studies which found value of agricultural product to be a major factor influencing adoption technology relating to production of such product (Kijima et al., 2011).

Farm visits as endogenous variable

The effect of heath care visit is positive and significant. Marginal effects show that an increase in farm health care visits by one unit increases adoption likelihood. The number of farm health care visits is confirmed to be endogenous, since the residue from the first regression is found to be significant. The distance to the market is used as the instrumental variable and confirmed to be a valid instrument. This is through weak instrument and over-identification test. Farm visits is one of the methods used to disseminate information about technology. Animal care workers focus on delivering key messages to farmers on each visit, this may start with basic information before moving on complex messages on subsequent visits. Therefore, with increased number of visits farmers get to learn more. Feder et al., (1985) pointed out that adoption is an outcome of a dynamic decision-making process that includes learning about the technology through the collection of information and this justifies the positive relation between farm health care visit and technology adoption.

Conclusion

The purpose of this chapter was to examine the determinants of adoption of improved dairy breeds by smallholder farmers in Kenya. The study established that social effects and production risks play a critical role in the adoption of improved breeds. This was demonstrated by positive and significant of exogenous effects as measured by the averages of the reference group schooling and income. Endogenous social effects as measured by the proportion of adopters in the reference group are also positive and significant. Risk was also found to be an important factor that influences adoption of agricultural technologies. This conforms with findings from various studies that attributed the low adoption of high yielding agricultural technologies to risk-averseness among farmers. In this study risk as measured by second and third moments of output is found to have a negative effect on adoption of improved breeds. The variance as measured by second moment is significant at one percent level. This study has demonstrated that risks and social interactions play a significant role in adoption of improved dairy breeds. This has important implication for policy makers in that many studies on the determinants of technology adoption do not take in to accounts risks and social interactions ignoring these vital factors could lead to the formulation of policies that are short of important aspects. It is clear from the results that it important to include production risks when designing and disseminating agricultural technologies to smallholder farmers since risk influence technology adoption. As (Groom et al., 2008) observed policymakers who model risk preferences incorrectly, wrongly predict the magnitude and direction of responses and therefore the impact of such policy. New technologies entail some risks and resource constrained farmers may be wary of taking up such technologies. Therefore, policy makers should play a role in helping farmers make informed choices especially on complicated matters such as where risks are involved. The results of this study also demonstrated how social interactions influence adoption of improved breeds positively. In absence of strong farm extension services like in the case of Kenya, social interactions among smallholder farmers should be must be promoted and enhances in order to facilitate knowledge sharing about technologies by farmers.

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