Agricultural Science Research Journal
ISSN 2026-6073
George Marechera et al, Volume (9) Issue (5): 47 – 60 July – 2019.
RESEARCH PAPER

Duration analysis of *DroughtTEGO*® hybrid maize adoption in Kenya

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Abstract

Previous studies have modelled determinants of adoption of new technologies, through static models, these models are inadequate in explaining the dynamic process of technology adoption. In this paper duration model is applied to capture the speed of the *DroughtTEGO*® hybrid maize adoption using a sample of 642 maize growing households. The result from descriptive analysis showed a high rate of awareness of *DroughtTEGO* varieties (61%) and about 42% cumulative adoption, with about half of the farmers started adopting in the first two years after they became aware of the varieties. The results further revealed, age of household head, dependency ratio, on-farm demonstration, women controlling household resource, and household income as the major factors that accelerate the adoption. In contrast, variables found to delay adoption were household and land sizes. There was also evidence that education, gender, record keeping and information from extension officer had no statistical influence on speed of adoption of *DroughtTEGO* seed. It was concluded that to accelerate large-scale *DroughtTEGO* hybrid adoption requires policies that; promote expansive on-farm demonstrations and the associated field-days, especially for young farmers; involvement of women in decision making particularly in farm resource allocation; and deliberate targeting of young farmers and those with large farms in deployment efforts.

Keywords: Adoption speed, Adoption policies, Drought tolerance, Duration analysis, Maize farmers, DroughtTEGO

Introduction

In Kenya, Maize (*Zea mays* L.) is one of the most important crops and is considered an essential food crop. It accounts for about 65% of total staple food caloric intake and the main source of income and employment for most households. Annually, over six million tons of maize are produced; and the farming households consume 75% of these.

The production of maize has shown an increasing trend due to both land area and productivity (FAO, 2016) mainly in response to the local demand. The main growing counties under this ecology include; Kakamega, Vihiga, Narok, Busia, Siaya, Homa-Bay, Migori, Kisumu, Nyeri, Meru, Embu, Machakos, Kitui, Tana River, Muranga, Bomet and Isiolo counties.

In 2012, African Agricultural Technology Foundation (AATF) launched an initiative to introduce and promote *DroughtTEGO* maize hybrid seed. The hybrids are drought-tolerant and were developed by the Water Efficient Maize for Africa (WEMA) Project with other partners (Oikeh et al. 2014; Edge et al. 2018). The details about the different varieties and strategies used by the project to enhance adoption have been comprehensively documented (Edge et al. 2018; Macharia et al., 2017; CropLife, 2017; Oikeh et al. 2014).). On farm research results indicate that *DroughtTEGO* varieties produce about 4.5 tons/ ha when compared with 2008 commercial varieties that yielded on average 1.8 tons/ ha drought (Situma, 2018). Thus, speedy adoption of these varieties is desirable since they increase production even under drought weather conditions.

Several studies carried out factors that affect adoption of agricultural technologies have largely been determined from studies that used static frameworks (Asfaw et al., 1997; Doss et al., 2003; Feleke and Zegeye, 2006; Ouma and DeGroote, 2011, Ragasa et al., 2013, Schroeder at al., 2013, Getacher, et al., 2013; Teklewold, et al., 2013). However, it is important to note that the static approach does not consider the dynamic environment in which the farmers make the adoption decisions. They only explain why farmers have adopted a given technology at a particular time, but do not explain why some farmers adopt earlier and others later. Again, static frameworks cannot assess the influence on adoption of time-dependent variableswhich by nature change over time.

Duration modelling which are non-static are better than static modelling, because they can look at the dynamic aspects of the adoption decisions. These models can determine what factors influence the probability of adoption and the time span to adoption (Dadi et al., 2004; D'Emden et al., 2006). However, despite the importance of speed of adoption, no study in Sub-Saharan Africa (SSA) or Eastern Africa has looked into factors that affect the speed of the adoption of seed-based technologies including *DroughtTEGO* maize hybrid seeds.

In general, duration modelling captures both the distinguishing features of duration data; that is; censoring and time-dependent variables in a relatively simple and flexible manner. Further, duration models also control unmeasured heterogeneity (Deaton, 1997and Butler and Moser, 2010). Another advantage of the hazard model is the ability to control for unmeasured heterogeneity without the need for a full panel data set.

Some studies reported by Fuglie and Kascak (2001), Burton et al. (2003), Dadi et al. (2004), Abdulai and Huffman (2005), D'Emden et al. (2006), Carletto et al. (2010), Pornpratansombat et.al. (2010), and Murage et al. (2012) have shown that the time taken by farmers to adopt an introduced technology can be influenced by various factors. In particular, access to information is critical in speeding up the adoption process.

Therefore, understanding how different information sources affect the speed of technology uptake is important in designing and selecting appropriate dissemination strategies for up-scaling and out-scaling *DroughtTEGO* adoption. The objective of this study, therefore, was to examine the effects of various dissemination pathways on the speed of adoption of *DroughtTEGO* while controlling for other socio-economic and institutional factors.

Methods

Theoretical framework

Suppose a farmer is faced with two competing technologies: an existing old technology (Old) and a newly developed technology (New). If the profits of both technologies are random, i.e., both technologies are risky assets for farmers, they will adopt the technology that they expect to give the maximum profit. That is, the farmer will adopt the technology that is perceived to achieve his or her objectives (Pannell et al., 2006). Hence, for the farmers to adopt the new technology, they must be able to gain more benefit (U_n) than the benefit (U_o) from non-adoption. Thus, the optimal decision is to adopt if U_n is greater than the benefit from the existing technology (U_o).).

$$U_o,\ U_n > U_o \qquad (1)$$

For an individual farmer, the decision to adopt is not only influenced by one variable but many variables, hence the probability of adopting a new technology is given as:

$$P_d = f\,(X,\ Y) \qquad (2)$$

Where P_d is the probability of adopting *DroughtTEGO,* while, X represent the vector of cross-section and time-dependent variables, and Y is the vector of both time-dependent and cross-section independent variables that describes the attributes of technology.

Duration Analysis (DA) is conducted to capture time-dependent variables. Duration analysis is also called survival analysis, transition analysis, failure time analysis or time to event analysis. The key element considered in duration analysis is the time (*T*) an individual spends in one state before transiting to another state. In our context, this transition startsstarts from the moment the household (farmer) learns about the *DroughtTEGO* until the time adoption took place. Therefore, in duration analysis, time (*T*) is always a non-negative variable that represents the length of time farmers waited before adopting the technology. The distribution of *T* is expressed by the following cumulative density function:

$$F(t) = Prob(T \leq t) \quad (3)$$

Where, *'t'* represents the cross-section of durations at t_1, t_2,…, t_n. The probability of an individual not adopting until or beyond time *t* is given by the survival function below.

$$S(T) = Prob(T \geq t) = 1- F(t) \quad (4)$$

Because of cumulative distribution function that is in-built within the survival function and due to the fact that *T* is always non-negative, it then follows that the function must satisfy S(0) = 1, S(∞) = 0. The above survival function requires a hazard rate *h(t)* specification that is instantaneous on the rate of adoption and is formally given as:

$$h(t) = \lim_{\Delta t \to 0} \frac{\Pr(t \leq T \leq t + \Delta \mid T \geq t)}{\Delta t} \quad (5)$$

The *T* in the above equation is assumed to lie between *t* and *t + Δt,* conditional on *T* being greater or equal to *t*, divided by the interval, as *Δt* goes to zero. The analysis model can then be represented as:

$$\alpha (t) = f(Xt\beta) \quad (6)$$

Where *X* are variables that influence the hazard rate and time-dependent covariates, while *β* are regression coefficients. With an assumption that a particular probability distribution for α gives a likelihood function that is maximized to generate *β* parameter for use. However, as discussed previously censoring in our case is an unavoidable problem.

Parametric, semi-parametric and non-parametric duration models have been applied in many studies that aimed at determining the duration for occurrence of an event in terms of compelling and influencing factors (Aryasepehr et al., 2002). Generally, parametric models are more efficient in their use of data as compared to non-parametric, because they do not reject what happens to covariates where adoptions occur.

Exponential, Weibull, Gompertz, logistic, lognormal and log logistic probability distribution are the renowned functional forms that have been utilized for parametric duration models (Kiefer, 1988; Cleves et al., 2004). However, the most parametric specifications commonly applied in the duration models are the Weibull and the exponential distributions. In our case, Weibull distributions were employed.

Surveys and data

Quantitative and qualitative data was used for this study from both sampled households and key Stakeholders' / informants'informants' interviews. A multi-stage, clustered, randomized sampling procedure was used. Although maize is grown in most parts of Kenya as indicated in the introduction, this study focuses on the five major maize growing regions namely Western Kenya, South Rift, Central Highlands, Upper Nyanza and Lower Eastern (Figure 1), because these are the regions where most of the *DroughtTEGO* hybrids dissemination activities are located.

Partly due to logistical and statistical considerations, the decision was taken to interview proportionate number of maize farmers in each of the five focus regions, giving 642 maize farmers.

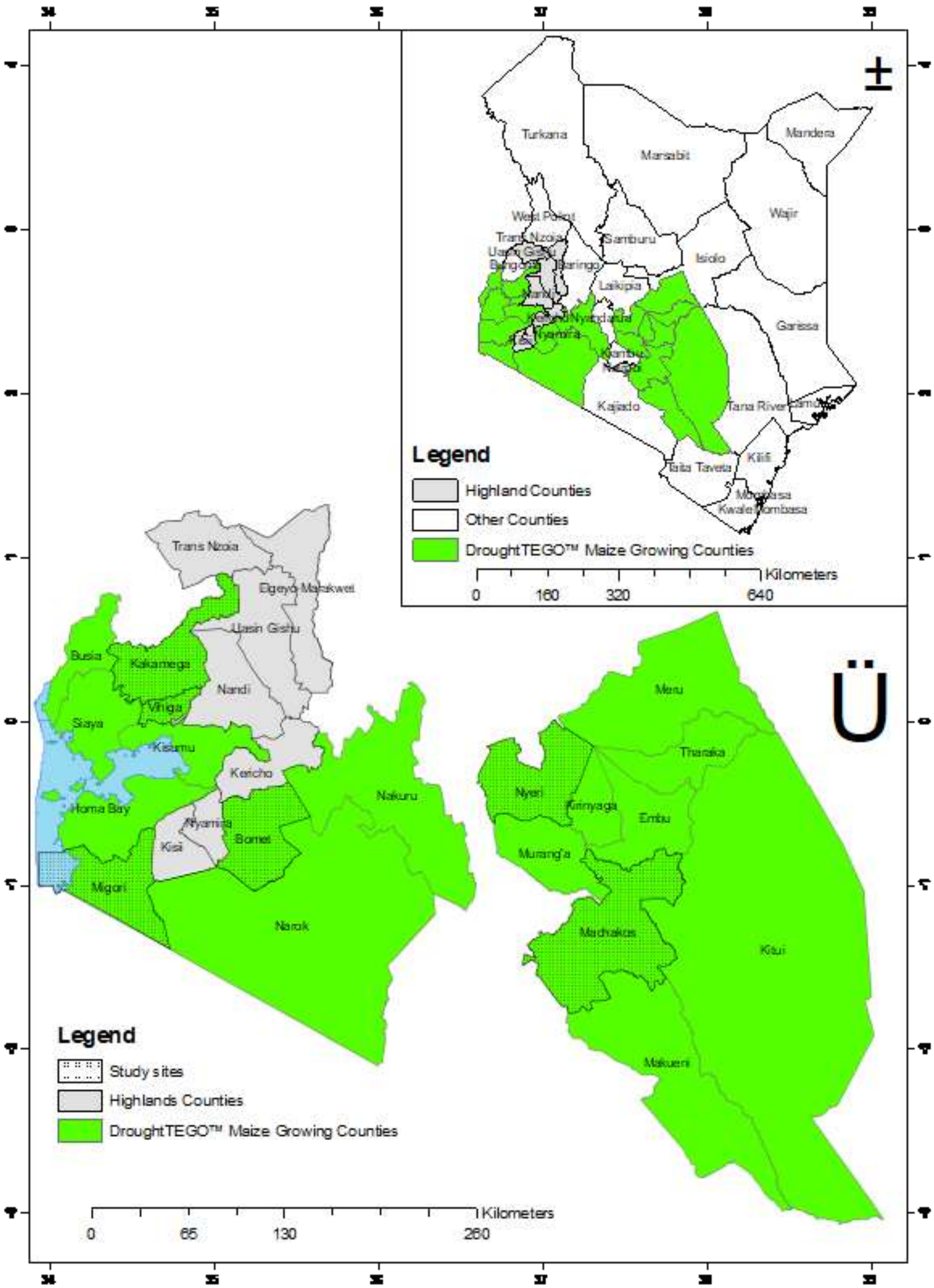

Figure 1: Map showing the ***DroughtTEGO*** growing counties and the study counties
Source: this study, 2017

The number of farmers interviewed in each region was determined by the maize production statistics in the area and the population. Within the regions, counties (one per region except for Western Kenya where the WEMA Project covers extensive area and more counties, hence two counties were selected randomly (Table 1).

Table 1: Regional distribution of survey respondents

Region	Counties	Sampling Sub-Counties	Sample size based on County proportion
South Rift	Bomet	Bomet	102
Western Kenya	Vihiga	Sabatia	75
	Migori	Rongo	135
	Kakamega	Kakamega	60
Upper Eastern	Nyeri	Mukurweini	170
Lower Eastern	Machakos	Kangundo	100

Source: this study, 2017

Probability Proportional to Size (PPS) sampling technique using the number of counties per region as strata was applied to arrive at sample size per region. Within each identified county, a sub-county was randomly sampled. At the regional level, farmers were sampled from sub-counties with significant maize production based on figures from the Statistical Unit of the Ministry of Agriculture, Livestock and Fisheries (MoALF) and AATF. In some instances, due to unavailability of sampling frames, the households were randomly sampled through random transect walks.

At the sub-county level, one administrative location was selected purposively, and villages were selected with the help of AATF field staff and county officials. To enhance data validity and reliability, intensively trained enumerators using a questionnaire developed by the researcher interviewed farmers. The interviews were conducted in January 2017. To maintain uniformity, data from all regions were transmitted to a host server where they were checked daily and corrective measures undertaken. The study utilized the Open Data Kit (ODK) whereby data was collected on a mobile device and transmitted to an aggregation server. The household-level data collected included gender, age and education level of farmer; household size, and membership to a farmers' organization. Additional information collected were accessibility to extension services, and knowledge of varieties planted by each farmer. Farm-level variables collected included size of the farm, crops grown, soil quality, distance of irrigation water source, type of maize seeds used by farmers, access to information on *DroughtTEGO* maize seeds, methods of technology transfer; and advantages and drawbacks of using *DroughtTEGO* maize seeds, food consumption and food security; and perceptions of changes in farm productivity and income.

Global Positioning System (GPS) was used to capture the precise location/coordinates of the sampled households and hence digitally mapped all the households/villages visited in the survey. Key stakeholders consulted included county officials, MoALF staff, AATF field staff, farmers hosting maize demonstration sites and agro-dealers. Data was then analyzed using Stata version 13.

Empirical Methods

The present study utilizes Duration Model. The dependent variable in our model is the number of years it took from the time the farmer heard about the *DroughtTEGO* varieties until the time adoption occurs. Important to note that by the time of the survey, there were some cases, where farmers had heard but they had not adopted the technology and the adoption time was unknown; and thus right- censored, therefore had no "failure times."

Non-parametric estimation was conducted before the parametric model estimation to investigate duration data without making any assumptions regarding the underlying distribution of survival or waiting times. The choice of explanatory variables was pegged on related studies and economic theories. Table 2 present the specific variables that were hypothesized to influence the speed of adoption. Expected direction of influence of those variables is briefly discussed below.

Table 2: Description of variables utilized in the duration estimations with expected sign

Variable	Definition	Sign
Demographic characteristics		
AGE	Age of household head (years)	+
EDUCATION0	1, if household head has no formal education; 0, otherwise	-
EDUCATION1	1, if household head has primary education; 0, otherwise	+
EDUCATION2	1, if household head has secondary education; 0, otherwise	+
EDUCATION3	1, if household head has > secondary education; 0, otherwise	+
GENDER	1, if the household head is male; 0, otherwise	+
HHSIZE	Number of family members living in the household in adult equivalent (count)	+
DRATIO	Dependency ratio (proportion over 64 and under 18years of age (%)	+
Access to information		
RADIO	1, if main source of information is radio; 0, otherwise	+
EXTENSION	1, if main source of information is government extension; 0, otherwise	+
FARMER	1, if main source of information is another farmer; 0, otherwise	+
DEMOS	1, if main source of information is demonstration and field trials; 0, otherwise	+
Asset endowment		
FARMSIZE	Farm size (ha)	+
INCOME	Total income (Ksh)	+
Other variables		
RECORD	1, if the household keeps farm records; 0, otherwise	+
WOMEN	1, if women control household resources; 0, otherwise	+
PRICE	1, if farmer perceives the *DroughtTEGO* seed to be expensive; 0, otherwise	
County dummies		
Migori	1, if the farmer is in Migori; 0, otherwise	
Bomet	1, if the farmer is in Bomet; 0, otherwise	
Nyeri	1, if the farmer is in Nyeri; 0, otherwise	
Vihiga	1, if the farmer is in Vihiga; 0, otherwise	
Kakamega	1, if the farmer is in Kakamega; 0, otherwise	

Source: Survey results, 2017

The household characteristics hypothesized to influence the adoption of *DroughtTEGO* varieties included: 1) age of the household head (AGE); 2) education level (EDUCATION); 3) gender of the household head (GENDER); and 4) dependency ratio (DRATIO). Labor availability is included by considering available family labor (HHSIZE). Access to information on improved technologies captured through: 1) contacts with extension officers (EXTENSION); 2) other farmers as main source of information (FARMER); and 3) field demonstrations of varieties and associated field- days (DEMOS) variables.

Lack of cash or credit can significantly affect the adoption of improved technologies; hence, asset endowment is included through two proxies' variables: 1) total land size (FARMSIZE) and 2) household total income (INCOME).

In this study, income derived from maize production was deliberately excluded to avoid problems of endogeneity. Other variables included were: 1) record keeping (RECORD); 2) maize as the main staple food (STAPLE); 3) own production of staple food (OWN); 4) food security in the last two years (FOODSEC); 5) women control of the household resources (WOMEN), 6) perception of seed prices (PRICE); and 7) county dummies.

Conventionally and in many research studies, it is generally considered that age is negatively related to adoption. This assumes that with age, farmers become more conservative and less amenable to change (Macharia et al., 2013). On the other hand, because age is sometimes taken as a proxy for experience, it is argued that with age farmers gain more experience and acquaintance with new technologies. Hence, older farmers are expected to use new technologies more efficiently as compared to younger farmers. However, there is a certain age (54) beyond which, farmers ability to take risk and engagement with innovations decreases. This means that young energetic farmers are more likely to take risks that are associated with new technologies such as yield uncertainty as compared to their older counterparts. Therefore, the AGE variable is hypothesized to have a positive sign. Age of the household head in this study was assumed to be constant since the changes for all household heads are parallel and it is the -cross-sectional variances that matter in this case.

Education enhances the ability of farmers to acquire and synthesize new information. Thus, education increases the probability of adoption of a new technology. It is also argued that the skill obtained through education can be spread to other members of the household. In fact, Weir and Knight (2000) showed that education is associated more with timing of adoption than with adoption itself.

Household size (HHSIZE) is in most cases used as proxy to account for labor availability. In general, a farm with larger number of workers is more likely to adopt new technologies that require more labor. In addition, in areas where labor markets are not well developed, family labor becomes an important determinant of technology choice since alternative technologies have different labor use intensity. However, it is important to note that, the effect of household size on improved technologies adoption can be sometimes ambiguous as household that are very poor may use their financial resources for family commitments with little left for the purchase of improved seeds or complementary inputs. On the other hand, it can also be an incentive to adopt improved technologies, as more agricultural output is required to meet the family food consumption needs. In some other instances, labor constraints may be a motivation to adopt time saving technologies. Thus, household size (HHSIZE) and dependency ratio (DRATIO) were both hypothesized to increase adoption.

Household wealth and farm characteristics variables considered to influence adoption of *DroughtTEGO*® maize seeds include farm size (FARMSIZE) and total income (INCOME). Farm size in most of the societies in Sub-Saharan (SSA) is used as a proxy for wealth. Thus, farmers with larger land size are assumed to have capability of purchasing new agricultural technologies because they can afford and can also bear the risk in case of crop failure. This means that farmers who have relatively large farms will be more likely to adopt *DroughtTEGO* maize seeds and vice versa. Wealth may also be an indicator of a farmer's access to credit.

Income enhances a farmer's ability to farm. Income earned outside the farm increases the farmers' financial capacity and increases the probability of investing on new technologies. According to Mathenge and Tschirley (2007) imperfect credit markets can be compensated by off-farm income which provides ready cash for input purchases and can be used to spread the risk of using improved technologies. Macharia et al. (2013) indicated that, external sources of income provide the means to acquire new technologies. However, opposite effects have been reported by Mbaga-Semgalawe and Fomer (2000). In this study, it was hypothesized to affect adoption positively.

Information about the new technology is a perquisite for adoption. Information also reduces the uncertainty about a technology's performance; hence, may change individual's assessment from purely subjective to objective over time (Caswell et al., 2001). Information is acquired through both informal and formal sources such as the media, extension personnel, visits, Barraza, demonstration sites, meetings, and farm organizations and through formal education. Awareness of the *DroughtTEGO* variables (EXTENSION, FARMER, DEMOS) are hence expected to have positive influence on the adoption of those varieties.

Empirical Results and Discussion

Non-parametric Duration Analysis

The result from descriptive analysis showed a high rate of awareness of at least one *DroughtTEGO* varieties (61%) and about 42% cumulative adoption, with about half of the adopters started adopting in the first two years after they became aware of the varieties, an indication that the varieties have penetrated the area.

All variables used in the models were all checked for multi-collinearity, heteroscedasticity model specification and endogeneity. Variance inflation factor and correlation tests revealed that the variables there was no serious multicollinearity observed (VIF < 5 and correlation coefficients < 0.4; none-significant for any of the independent variables). Similarly, for endogeneity checks none of the independent variables was suspected to be explained within the equation utilized.

Following Akaike (1973), both Weibull and Exponential models were estimated and Akaike Information Criterion (AIC) test used to select the model of best fit. The exponential model had an AIC of 134.26 while Weibull model registered lower AIC value of 91.24, an indication that the Weibull model best explained our data on duration dependence. At time t = 0 (2013) the functions take value 1 since no farmer had adopted the *DroughtTEGO* hybrid seeds.

The horizontal axis in Figures 2 and 3 is the analysis time that starts from the year when *DroughtTEGO* was first introduced (2013) to the year when the data were collected (2016). As previously explained, when time *t* is equal to 2012, the axis takes a value of 1 since no farmer has yet adopted. Figures 2 shows that the speed of adoption was initially high closer to almost 50% in the early stages, an indication of a quick adoption during the first two years but dropped to about 26% and decreased constantly thereafter.

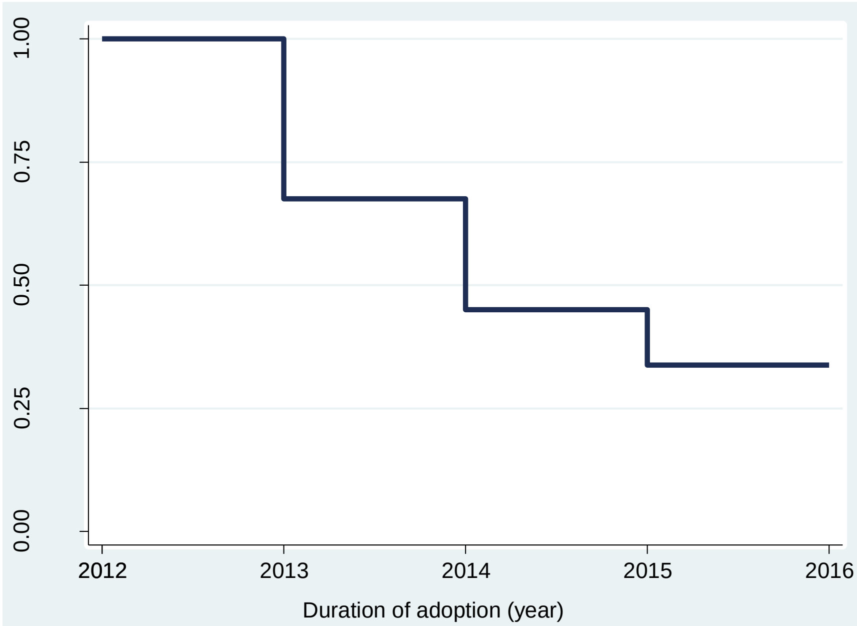

Figure 2: Kaplan-Meier survival estimate

Figure 3 gives the information on survival time separated by county. The adoption time of Kakamega seems to be high when compared with the other counties, while that of Migori was the lowest. This suggests that farmers in Kakamega are early adopters followed by those at Nyeri. Again, the speed of adoption for all counties proceeds at a persistent rate until the fourth year.

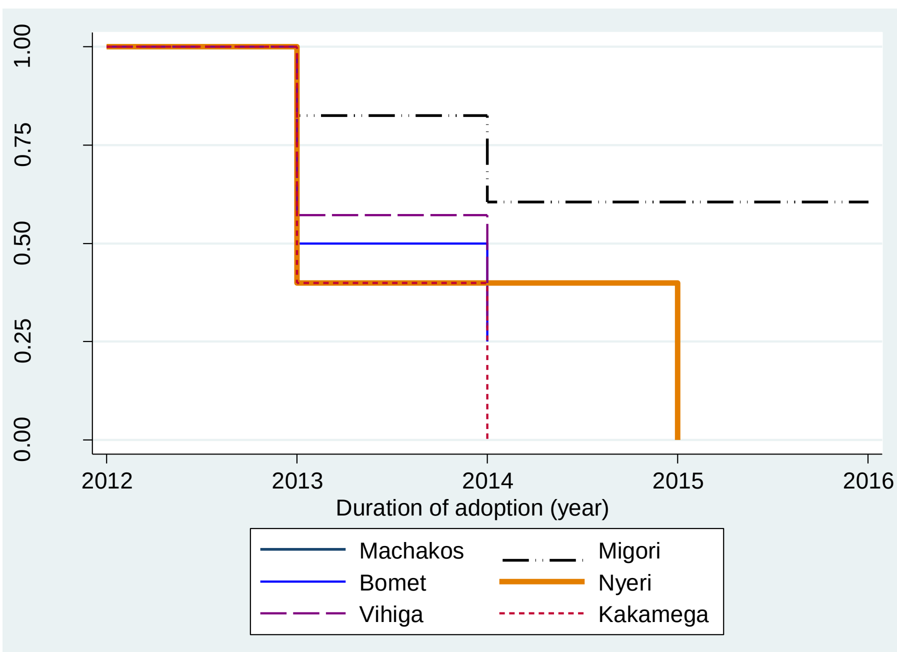

Figure 3: Kaplan-Meier survival estimate disaggregated by county

As illustrated in Figure 4, it was clear that male farmers were more likely to adopt *DroughtTEGO* faster than their female counterpart. However, the trend shows a close-up relationship for late adoption as it approaches the 4th year.

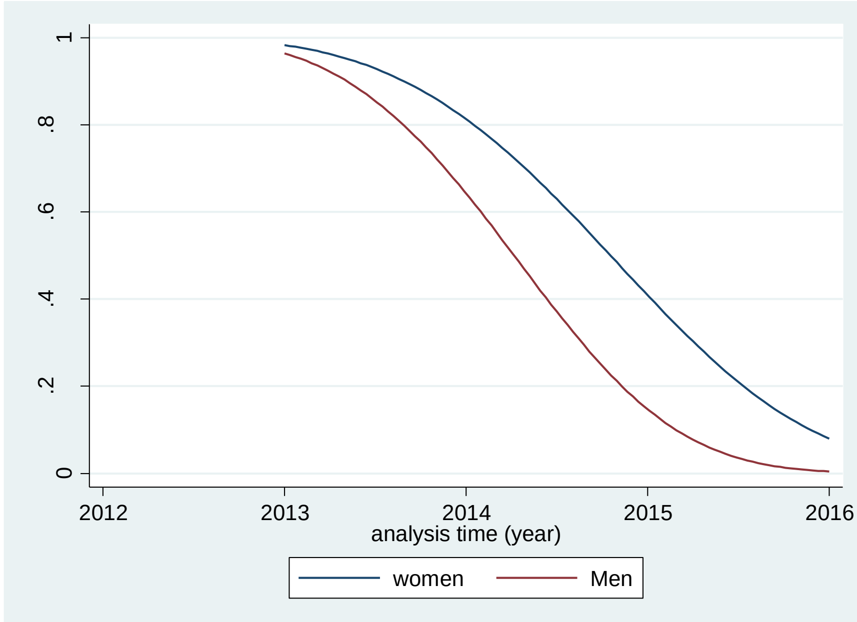

Figure 4: Survival time by gender of household head

Parametric Duration Analysis

Hazard ratios from the duration analysis are reported in Table 3 below. In general, coefficients that are below one (1) indicate a longer pre-adoption spell and consequently lower probability of adoption. While, a coefficient greater than unity (1) is an indication of a faster adoption, whereas a hazard ratio of exactly one (1) implies no impact of the variable on adoption.
On the marginal effects (column 3 in Table 3), coefficient that are negative for any of covariate indicate a faster adoption as it indicates negative marginal effect on duration, while positive coefficient implies slow adoption rate. From Table 3 age of household head (AGE), household size (HHSIZE), dependency ratio (DRATIO), on-farm demonstrations and associated field-days as the main source of information (DEMOS), women control of household resources (WOMEN), household income (INCOME), and farm size (LAND) significantly affected the speed of *DroughtTEGO* adoption.

Table 3: Weibull model estimated coefficients for the adoption of ***DroughtTEGO*** Varieties

_t	Hazards Ratio	Std. Err.	ME	Std. Err.
AGE	1.09	0.02***	-0.07	0.02***

EDUCATION1	0.21	0.25	1.27	0.95
EDUCATION2	0.17	0.24	1.43	1.11
EDUCATION3	0.39	0.63	0.76	1.29
HHGENDER	1.68	1.12	-0.42	0.54
HHSIZE	0.78	0.07***	0.20	0.09**
DRATIO	1.04	0.02**	-0.03	0.01**
RADIO	1.85	1.52	-0.50	0.66
EXTENSION	0.22	0.22	1.23	0.81
FARMER	0.27	0.32	1.05	1.05
DEMOS	9.00	7.13**	-1.77	0.74**
LAND	0.72	0.13*	0.27	0.17*
INCOME	1.00	0.00***	-0.00	0.00***
RECORD	0.55	0.42	0.48	0.62
WOMEN	3.71	2.38**	-1.05	0.56*
PRICE	1.94	1.82	-0.53	0.77
_cons	0.00	0.00		
/ln_p	1.23	0.14		
p	3.43	0.49		
1/p	0.29	0.04		

Age of farmer (AGE) is statistically significant and has hazard ratio that is more than one (1), indicating that a one-year of additional age increases the hazard rate of adoption by about 9%. Again, the negative marginal effect for age implies that older farmers can take up the technology much faster compared to young farmers. Normally, farmers' age and adoption of the new technology are inversely correlated (Macharia et al., 2013). This finding is contrast with the report of Matuschke and Qaim (2008) who found age of household head had a significant effect on accelerating the adoption of pearl millet in India.

However, this is not the case in this study and probably the elderly farmers could have accumulated capital that makes it possible to have cash income required to purchase technology faster than the younger ones. Older farmers are also likely to adopt a technology because of their accumulated knowledge and experience (Lapar and Pandey, 1999; Abdulai and Huffman, 2005).

Contrary to expectation, household size increased the duration to adoption by 20%, suggesting that farmers who had bigger household delayed decision to adopt. The result does not corroborate with those of Croppenstedt et al. (2003) who found that households with a larger size of household members were more likely to adopt agricultural technology and use it more intensively because they had enough labour. But it confirms the notion that the adoption of seed technologies is not affected by labour supply unlike labour intensive technologies like manure or fertilizer application.

As expected, the marginal effects for dependency ratio is negative, an indication that it hastens the rate of *DroughtTEGO* adoption. This finding is consistent with the empirical studies of adoption of agricultural innovations using duration analysis, because it is an incentive to adopt improved technologies, since more agricultural outputs are required to meet the family food consumption needs.

The speed of adoption was significantly faster by about 77% among farmers who attended or participated in on-farm demonstration trials and the associated field-days while it slower amongst farmers who sourced information from radio and other farmers. This implies that the speed of adoption is influenced by the information sources used. The decrease in duration of adoption through on-farm demonstrations as the main source of information is consistent with the popular saying that "seeing-is-believing", where people generally tend to believe and accept what they practically see and touch. This is even more so when it comes to new seed technology that is different from known varieties of seeds that famers are used to. Thus, farmers were unwilling to adopt *DroughtTEGO* until evidence indicated the profitability or the benefit in doing so. Previous studies by Yishak and Punjabi (2011) and Dadi et al. (2004) also reported similar result that participation in on-farm demonstrations decreased the time to adoption of new varieties.

The hazard ratio for land size was less than unity and the corresponding marginal effects indicated that land size delayed adoption of *DroughtTEGO* by 27%. This is in contrast with studies by Roy et al. (1999), Yishak and Punjabi (2011) who reported that farmers with large farm size are more likely to adopt improved maize varieties. Further, studies by Workneh and Michael (2002) also reported positive relationship between farm size and technology adoption. However, research by Bradshaw et al. (2004) found mixed results with both negative and positive effects of farm size on the adoption of agricultural technologies, an indication that the effect of farm size on technology adoption is inconclusive.

The negative marginal effects of income level was highly significant and implyimply that farmers with higher income can take up the seed technology earlier because of higher purchasing power compared to those with lower income. Results also showed that households where women control resources significantly enhanced rapid adoption of *DroughtTEGO*. Previous research in Africa had documented that women have lesser access to and control of critical resources, especially land, cash, labour and information (Quisumbing et al., 1995, Kaliba et al., 2000) which could slow their adoption of technologies.

Contrary to expectations, and perhaps more informative finding, is that factors such as education, gender, record keeping and information from extension officer had no significant influence on speed of adoption of *DroughtTEGO* varieties in this study (Table 4). However, other studies indicated that decrease in price of a technology favoursadoption speed (Marsh et al., 2000; Yishak and Punjabi, 2011). Burton et al. (2003) observed marginal but insignificant impact of higher education on the hazard. Education enables farmers to distinguish more easily technologies whose adoption provides an opportunity for net economic gain from those that do not (Abdulai and Huffman, 2005).

Conclusions and recommendations

This study has conveyed information on the factors that affect the duration of *DroughtTEGO* hybrid seed adoption in Kenya. Descriptive analyses suggest that farmers' adoption behavior can be classified as early adopters, late adopters, and none-adopters. The adoption status of farmers also varied by gender and location. Accordingly, male households and farmers at Kakamega and Nyeri counties have the characteristics of early adopters as compared to their counterparts in other major maize growing agro- ecologies in Kenya. The main variable found from the duration model to hastened adoption was; age of the household head, dependency ratio, on-farm demos and associated field days as the main source of information, women who control household resources, and household income. In contrast, variables found to delay adoption were household size and land size.

The variables that were found to have no significant association with speed of adoption included education level, gender of the household head, main source of information from government agents, radio and other farmers, and price of the seeds. This study, therefore suggests that measures to promote speedy adoption of *DroughtTEGO* hybrids and other seed technologies fall primarily under the expansion of on-farm demonstrations and the associated field-days, encouraging women farmers to control household resources, and promoting other activities such as diversification that boost farm income. In addition, it may be necessary to investigate the reason, why young farmers are not interested in this technology. Probably targeting those for on-farm demonstrations; and giving special attention to farmers with large farms could increase *DroughtTEGO* hybrids adoption. Again, due to the dynamic nature of decision to adopt agricultural technologies the study recommend application of duration analysis as the best means to analyse the time to adopt.

Future research in this area should address the speed of adoption of *DroughtTEGO* in relation to other competing varieties.

Acknowledgments

The funds used in carrying out the research were provided by AATF within the framework of the WEMA Project supported by the Bill and Melinda Gates, the Howard G. Buffett Foundation, and the United States Agency for International Development (Contract ID: OPP1019943). The support of the extension workers of the Ministry of Agriculture and Rural Development was also crucial in the data collection process. Special thanks are due to all farmers who spent their precious time in giving information during the survey and to Dr. Kiprotich Bett, Dr. Felix Ngetich and Ms. Milka Ngonyo who were co-partners at the initial research stages.

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