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Speed of adoption of improved maize varieties in Tanzania: An application of duration analysis

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ABSTRACT

Maize is a strategic commodity for improving food security and alleviating poverty in Tanzania, but its productivity remains low. The importance of improved maize varieties (IMVs) in increasing productivity is documented in existing literature. Previous adoption studies in Tanzania did not examine the factors that influence the speed/timing of adoption. This study examines the determinants of the speed of adoption of IMVs using a duration model and recently collected plot- and household-level data in rural Tanzania. The results highlight the importance of social capital and networks in speeding up the adoption of IMVs. Similarly, government extension workers as a main source of information have a positive effect on the speed of adoption. The regression results also suggest that rainfall and farmers' confidence in government support during crop failure speed up the adoption of IMVs. The findings imply that interventions that strengthen the role of extension services, rural institutions and networks can accelerate the adoption of IMVs by smallholder farmers in Tanzania.

1. Introduction

Maize is a staple food in sub-Saharan Africa where 95% of the maize produced constitutes a significant part of the daily diet (Høgh-Jensen et al., 2007). It is the primary food and cash crop grown in Tanzania, accounting for over 45% and 75% of the total cultivated land and cereal production, respectively (Shao, 2007). Over the last five decades the trend has been to increase the area of cultivated maize (Fig. 1). The annual per capita consumption of maize is around 115 kg; and because of its greater caloric density compared to other crops, maize is an important source of calories, contributing 33% of total household consumption (Minot, 2010; Otunge et al., 2010).

Despite the economic importance of maize in the national economy of the country, the sector is characterized by decades of stagnation and volatility in production and productivity (Fig. 1). Although there is an increase in total maize production over the years, most of the increase is due to area expansion. Between 1980 and 2010, there was only a marginal increase in maize productivity (Fig. 1). The low yield level is associated with a low level of adoption of technologies such as improved seeds and complementary inputs. In our sample, about 38% and 34% of farmers adopted hybrid fresh seeds and open pollinated varieties (OPV) seeds fresh and recycled up to three seasons, respectively. Only five percent of households used chemical fertilizer.

With areas of available arable land shrinking due to population growth, increasing productivity through expansion of agricultural technology is a key, and perhaps the only, strategy option for increasing agricultural production. Minton and Barrett (Minten and Barrett, 2008) argue that the adoption of agricultural technologies, with subsequent improvements in productivity, has the potential to increase food security for all sections of the poor. Net food buyers benefit from lower food prices while unskilled workers benefit from increased real wages. If output

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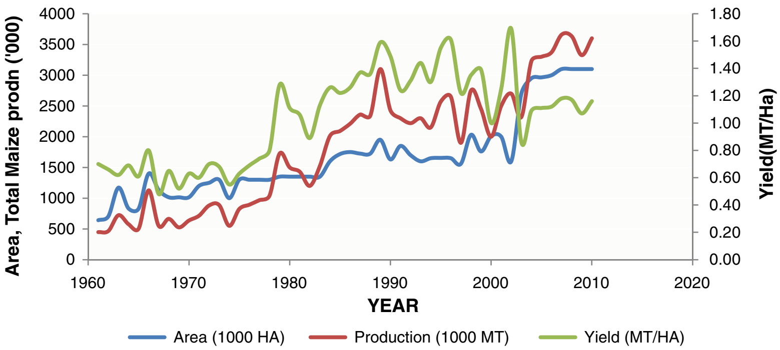

Fig. 1. Area cultivated, production and productivity of maize over time.

grows faster than price, net food sellers also benefit from farm profits. With almost all farmers in Tanzania growing maize, even small changes in the productivity of maize are likely to impact the lives of many poor farm households.

In Tanzania, improved agricultural technologies, including improved maize cultivars, have been stressed in key strategic documents as important tools for achieving reductions in hunger and poverty. However, despite several programmes and considerable efforts by organizations over the past decades, the adoption of improved technologies is low. A number of factors such as socioeconomic, institutional, cultural and policy conditions affect the ability of farmers to adopt technologies. A better understanding of the constraints that condition farmers' adoption behavior is important for designing and implementing policies that could stimulate the adoption of improved maize technology.

With few exceptions (e.g., (Dadi et al., 2004; Abdulai and Huffman, 2005; Matuschke and Qaim, 2008)), previous adoption studies (e.g., (Munasib and Jordan, 2011; Dimara and Skuras, 2003; Isham, 2002; Teklewold et al., 2013; Marenya and Barrett, 2007; Langyintuo and Mekuria, 2008; Bandiera and Rasul, 2006; Kaliba et al., 2000)) in developing countries fail to consider the timing of the adoption event and do not explicitly address the effect of explanatory variables on the time-path of adoption. Including the timing of an adoption can provide important information, particularly if adoption is related to specific events that occurred in the past or if time is considered to be linked to phenomenon-like learning by doing and learning from others (Matuschke, 2007). To bridge this gap duration, models are applied in this study. These models allow us to determine not only why farmers adopted a technology, but also on the timing of the adoption decision and what factors influenced the observed time patterns (Matuschke and Qaim, 2008).

Speed of adoption is desirable, since timely adoption of new technology can improve overall agricultural productivity and determine the survival of farms (Fuglie and Kascak, 2001; Batz et al., 2003). Production increases in the early years of adoption have a much greater impact on the rate of return on capital investment than increases in later years; thus with such rapid results policy makers are in a position to justify investments (Hazell and Anderson, 1986). Overtime, widespread adoption of new technology is likely to put downward pressure on product prices and upward pressure on the prices of purchased inputs that embody the new technology. This can adversely affect marginal farmers that have not yet adopted new technology or have done so less successfully (Fuglie and Kascak, 2001).

Using duration analysis to explore the factors that affect the length of time required for Tanzanian farmers to adopt IMVs, this paper contributes to existing literature in the following ways: firstly, it contributes to the limited literature on the application of duration analysis to agricultural technology adoption — to our knowledge, this is the first study to apply a hazard function to maize technology adoption; secondly, although there is well-developed literature on the impact of a host of explanatory variables on technology adoption, this analysis provides new evidence on the impact of policy-relevant variables such as social capital (e.g., the number of traders a farmer knows), and a farmer's expectations as regards social safety nets (social insurance) during crop failure. We also include technology information sources which are not available in most other similar studies. Thirdly, one of the major contributions of this study is the inclusion of how lag rainfall, which is a time-varying variable, can affect the decision to adopt IMVs. In Tanzania, rain-fed agricultural production dominates, which makes the country susceptible to extreme climate events. The knowledge and information obtained from this study may be useful in designing strategies that could speed up the adoption of private and public improved maize technologies by farmers.

The paper is structured as follows: the next section presents data and description of variables including the study area used in the empirical analysis; section three presents a detailed discussion about the econometric duration or hazard-rate model of adoption employed in the analysis; section four presents the results of the empirical analysis; and the last section concludes and draws policy implications.

2. Data and description of variables

Our data comprises information on 681 farm households collected across 60 villages in 4 districts of Tanzania. The data were collected by the International Maize and Wheat Improvement Center (CIMMYT) in collaboration with the Selian and Ilonga Agricultural Research Institutes between November and December 2010. Well-trained and experienced enumerators who had knowledge of the local language administered a structured survey questionnaire. The survey targeted the maize–legume farming systems of the eastern and northern zones of Tanzania.

A multistage sampling procedure was employed. In the first stage, four districts from two zones were selected based on their maize–legume production potential: Karatu and Mbulu from the northern zone, and Mvomero and Kilosa from the eastern zone. Each of the two zones was assigned an equal number of sample households. The households within a zone were distributed within the two respective districts according to the number of households in the district (proportionate sampling). The remainder of the sampling process was proportionate random sampling: 5–13 wards were selected in each district, 1–4 villages in each ward, and 2–30 farm households in each village.

Trained enumerators collected a wide range of information on crop varieties, adoption and information sources, the number of years the farmer had been aware of improved varieties, and household socioeconomic and plot characteristics.

Descriptive statistics for the dependent variable and the explanatory variables used in the analysis are presented in Table 1.

2.1. Dependent variable

The analysis is done at the variety level considering the period 1970–2010. The data contains multiple cases of awareness and/or adoption per farmer during the study period. There are different maize varieties known/heard of and adopted by farmers over different periods of time. The dominant varieties grown by farmers in the study areas are shown in Fig. 2. All the varieties except H 513 and Kito-ST are pest and disease resistant. The varieties H513 and Kito-ST are fairly resistant to moisture stress and SC 627 is also resistant to lodging.

The challenge with recall data is that respondents may state the number of years that they have been growing improved maize varieties incorrectly by rounding up or down. This may bias the variance of the parameter estimates, but estimates remain unbiased if response errors are uncorrelated with observed characteristics of the farmer (Matuschke and Qaim, 2008; Fuglie and Kascak, 2001).

In our study areas, most of the varieties were adopted recently. The data shows that only 5% of the total varieties were

Table 1
Descriptive statistics of variables used in the analysis (N = 1744).

Description of variables	Mean	S.D.
Dependent variable		
Adoption gap/length of adoption	2.90	4.20
Explanatory variables		
Household characteristics		
Sex of the household head (1 if male, and 0 if female)	0.90	0.30
Age of the household head at time of adoption (years)	41.52	13.61
Household head is illiterate (0–1 grade) (1 = yes)[b]	0.14	0.35
Household head completed primary (1–6 grade) (1 = yes)	0.16	0.37
Household head completed secondary (7–12 grade & above) (1 = yes)	0.70	0.46
Household size in adult equivalent	4.76	2.04
Number of years the HH lives in the village	33.84	15.85
Size of cultivated area in acres	4.14	4.55
Livestock owned in tropical livestock unit (TLU)	4.86	12.25
Per capita expenditure ('000)[a]	502.96	478.34
Access to services		
Distance to the main market from residence (in km)	16.34	16.63
Walking distance to the nearest seed dealer (in minutes)	141.85	111.02
Access to credit	0.14	0.35
Information source		
If main source of information on IMV is government extension[b]	0.24	0.42
If main source of information on IMV is relatives	0.27	0.44
If main source of information on IMV is neighbors	0.28	0.45
Social capital and network and trust indicators		
Number of grain traders in/outside the village that a household knows	5.80	5.16
Membership of rural institutions/group	0.33	0.47
Number of relatives living in the village	3.70	4.84
Government support during crop failure	0.33	0.58
Confident with skills of extension workers	3.61	1.42
Village level variables		
Annual rainfall (in mm) (time varying)	1047.99	1376.32
Cultivated area good/medium fertile (yes = 1, 0 otherwise)	0.87	0.34
If the farmer is located in Karatu district = 1, 0 otherwise[b]	0.28	0.45
If the farmer is located in Mbulu district = 1, 0 otherwise	0.24	0.43
If the farmer is located in Mvomero district = 1, 0 otherwise	0.18	0.38
If the farmer is located in Kilosa district = 1, 0 otherwise	0.30	0.46

[a] The exchange rate at the time of the survey was 1 USD ≈ 1490 TZS (Tanzanian Shillings).
[b] Reference group.

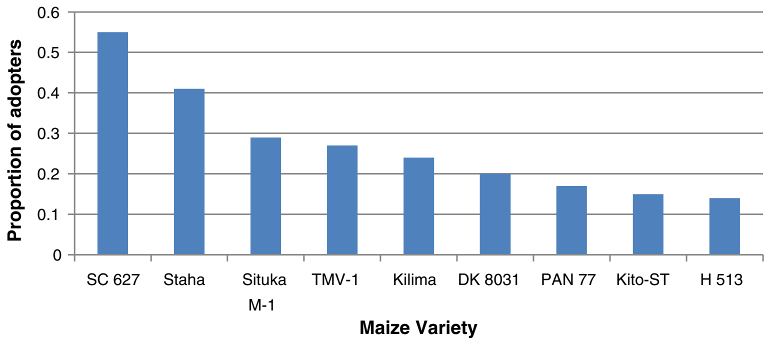

Fig. 2. Adoption pattern of major maize varieties grown by farmers.

adopted before 1990. Around 15% of the varieties were adopted between 1991 and 2000, while more than 78% were adopted between 2001 and 2010. This also holds true for the major improved maize varieties as shown in Fig. 3. Given that most households adopted the new variety recently; it may be easier for them to remember the year they heard and adopted the new variety for the first time. This may minimize errors/biases that can be stemmed from retrospective data.

The dependent variable in this study is the adoption gap/length of adoption of varieties: that is, the number of years the farmer waited between first becoming aware of a new maize variety and actually adopting it. Previous studies (e.g., (Dadi et al., 2004; Abdulai and Huffman, 2005)), considered the year the technology was introduced in the village as the time of first awareness, assuming that farmers in the village all became aware of the technology at the same time.[1] This approach may not reflect the real time the farmer waited to adopt the technology. For those farmers who had not yet adopted, the duration is right-censored at the year of data collection. The average number of maize varieties known/heard of by farm households was 3.63, while the average number of varieties planted by sample households was 2.17. The average number of years between the time a farmer first knew about or was aware of the IMV, and the time of adoption, was 2.89 years.

2.2. Explanatory variables

Following the duration adoption literature and economic theory (e.g., (Dadi et al., 2004; Matuschke and Qaim, 2008; Fuglie and Kascak, 2001; Burton et al., 2003)), the variables presented in Table 1 were used in the adoption gap analysis. We briefly describe below some of the variables that are not common in the literature.

The agricultural sector in Tanzania depends mainly on rainfall, and this has implications on agricultural technology adoption. Annual rainfall for the last 41 years (1970–2010) was collected in each district. The inclusion of the rainfall variable is one important contribution of this paper as it has not been addressed in other similar studies. We have rainfall data that varies by district and by year, that is, we have a time series data and this is related with the actual adoption period of the new maize variety. Lagged rainfall (lagged by one period) was considered in the analysis. We hypothesized that farmers who experienced good rainfall in the previous year are expected to adopt new technologies.

Recent empirical studies have shown the importance of social capital/networks and personal relationships on the technology adoption process (Isham, 2002; Bandiera and Rasul, 2006; Di Falco and Bulte, 2011). With scarce or inadequate information sources and imperfect markets, social networks can facilitate the exchange of information, enable farmers to access inputs on time, and overcome credit constraints. Social networks also reduce transaction costs and increase farmers' bargaining power, helping farmers earn higher returns when marketing their products. On the other hand, social capital such as more relatives in the village may discourage investment. This is the dark side of social capital (Di Falco and Bulte, 2011). We distinguished three social capital and network variables: a household's relationship with rural institutions in the village (1 if the household is a member of a rural institution/association and zero otherwise); a household's relationship with trustworthy traders (proxied by the number of trusted traders in and outside the village known by the household); and a household's kinship network (measured by the number of relatives that the farmer can rely on in times of need in the village). Different forms of social capital and networks may provide different services to farmers, but the expected effect on the adoption decision is therefore indeterminate *a priori*.

The speed of adoption can be influenced by the sources of the technology information available to farmers. It is crucial to identify which source of information is appropriate in technology adoption, since the role of information is a key area in which public policy can play a significant role (Lee, 2005). Cavane and Donovan (2011) in Mozambique found that farmers who learned from extension workers were more likely to adopt fertilizer than those who learned from neighbors. Krishnan and Patnam (2012) in Ethiopia found that learning from extension workers did not affect farmers' adoption of improved seeds and fertilizer, but learning from neighbors was a powerful force for adoption. Three sources of information are considered in this study: government extension workers, relatives, and friends. In our study sites, the majority of farmers get their information from farming relatives (27%) and neighboring farmers (28%). Government extension is the main source of information for about 23.5% of the sample households. In addition,

[1] In our case we were not able to find data on the year the varieties were introduced for the first time in each village.

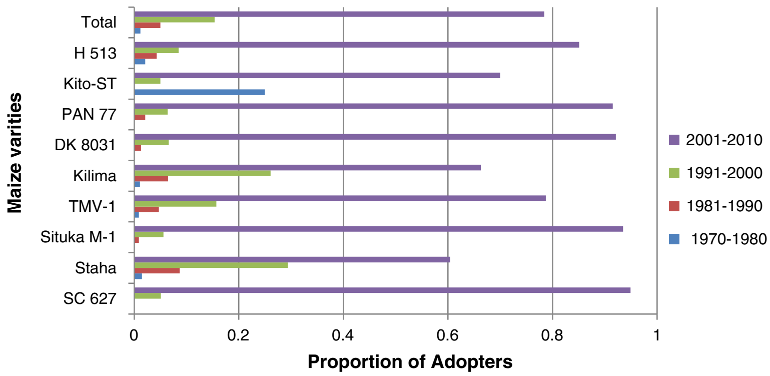

Fig. 3. Adoption of varieties by year.

farmers were asked about their confidence in the skill of extension workers, as extension contact *per se* may not lead to adoption of technology (Teklewold et al., 2013; Kassie et al., 2013). When households deal with competent extension agents, they may develop the confidence to adopt technologies, believing that competent agents will provide better services.

In most of the developing world where production risks are already high due to a number of factors, farmers are less likely to adopt risky technologies. If risk-reducing mechanisms such as subsidies, insurance and productive safety-net programmes are available to smooth consumption during crop failure, farmers are more likely to opt for practices which might bring a higher return, even if these are perceived as risky. We include a dummy variable taking a value of one if a household relies on government support during crop failure, and zero otherwise. Social safety nets/insurance, if properly implemented, can build the confidence of the farmer so that he or she invests despite uncertainty, and help farm households in smoothing consumption and maintaining productive capacity by reducing the need to liquidate assets or, alternatively, by reducing the need to sell labor that would instead be used on the farm (Barrett, 2005). Thus farmers' confidence in external public support can positively influence the adoption of IMVs.

Transaction costs play a significant role in the process of adoption/diffusion of agricultural technologies. For example, access to markets may influence the net benefits from the adoption of new technologies. Distance from the market can reduce the expected profitability of a new technology, since obtaining professional support and advice about the new technology becomes difficult, and access to complementary inputs becomes limited and costly (Abdulai and Huffman, 2005). Additionally, a greater distance to the nearest seed dealer creates a barrier associated with limited information about increased costs of screening, bargaining with, and monitoring distant trading partners. In general, when transaction costs are high, farmers tend to make decisions about allocating resources based on self-sufficiency rather than on maximization of profit, thus hindering the technological change process (Feleke and Zegeye, 2006). Most empirical studies also found a negative and significant association between market distance and adoption of new agricultural technologies (see for example, (Dadi et al., 2004; Abdulai and Huffman, 2005; Feleke and Zegeye, 2006)). Factors such as distance to output market and distance to seed dealer are included in our empirical analysis to see if they have a detrimental effect on the adoption of IMVs.

Other household socioeconomic characteristics included in the analysis are asset ownership (livestock and land), education, family size, age at the time of adoption, gender of household head, and access to credit. The inclusion of asset ownership and family size in the analysis is based on the hypotheses of the poverty trap. The poverty trap implies that households with initially low-income levels remain low-income households over a long period (Matuschke and Qaim, 2008). Further, major adoption has taken place recently (2001–2010). This indicates that farmers may not quickly change their asset endowments.

A land-quality variable representing the soil fertility status of the farmer's plot was also used in the analysis. It is equal to one if 50% or above of the farmland of the respondent had good or medium fertile soil and zero otherwise. Finally, district dummies to capture location-specific differences are included in the analysis.

3. Duration model of technology adoption

Duration analysis, commonly referred to as survival analysis, has been widely used in other areas of economics, with limited application in the analysis of agricultural technology adoption (e.g., (Fuglie and Kascak, 2001; Burton et al., 2003; Dadi et al., 2004; Abdulai and Huffman, 2005; Matuschke and Qaim, 2008)). The purpose of duration analysis is to understand the factors that explain the length of a spell, where the spell starts at the time when a farmer hears about or becomes aware of a technology for the first time, and the spell ends at the time a farmer adopts a technology.

Probability theory plays a fundamental role in duration analysis. Instead of focusing on the length of time of a spell, one can consider the probability of its end or the probability of transition to a new state. In a technology adoption study, the pertinent question would be: what is the probability of a farmer adopting a certain technology at time t, given that he or she has not adopted by that time (Burton et al., 2003)? This can be answered by the hazard function, defined below.

The duration model is specified as follows: Let $T \geq 0$ denote the duration, which has some distribution in the population, while t denotes a particular value of T. In survival analysis, T is the length of time a subject survives. In our case, it is the length of time, measured in years, until the household adopts the new technology. The cumulative distribution function (cdf) of T is defined as:

$$F(t) = \int_t^0 f(x)dx = P(T \le t), \quad t \ge 0 \tag{1}$$

Eq. (1) denotes the probability that the duration time T is smaller or equal to some value t.

Assuming that T is continuous and has a differentiable cdf, the survival function is defined as:

$$S(t) = 1 - F(t) = P(T \ge t) \tag{2}$$

$S(t)$ gives the probability that a duration will last longer than time t. In adoption study, the survivor function expresses the probability that an individual has not adopted an innovation at time t (Matuschke and Qaim, 2008).

Duration analysis centers on the hazard function. The probability of leaving the initial state in the interval $[t, t + h]$ given survival up until time t is given by:

$$P(t \le T \le t + h/T \ge t). \tag{3}$$

The average probability of leaving the state per unit of time period over a short time interval Δ, at or after t is:

$$\lambda(t) = \lim_{h \to 0} \frac{pr(t \le T < t + h/T \ge t)}{h}. \tag{4}$$

The hazard function can then be specified in terms of the density and distribution functions as:

$$\begin{aligned} &= pr(t \le T < t + h/T \ge t) = pr(t \le T < t + h)/pr(T \ge t) \\ &= \frac{F(t+h) - F(t)}{1 - F(t)}. \end{aligned} \tag{5}$$

When the cdf is differentiable, we can take the limit of the right-hand side, divided by h, as h approaches zero from above:

$$\lambda(t) = \lim_{h \to 0} \frac{F(t+h) - F(t)}{h} \cdot \frac{1}{1 - F(t)} = \frac{f(t)}{1 - F(t)} = \frac{f(t)}{S(t)}. \tag{6}$$

As defined before, $S(t)$ is the survival function which shows the probability that non-adoption of the technology will last at least until t. $f(t)$ is the probability density function. The hazard function specifies the instantaneous rate of completion of a spell at $T = t$ conditional upon survival up to time t. It is the rate at which spells will be completed at duration t, given that they last until t. In our case, the hazard function therefore represents the probability that a household adopts the improved variety at time t, given that it has not adopted before t. In this study, a higher hazard rate indicates a higher rate of speed of adoption.

A variety of functional forms have been proposed for duration models including the logistic, Weibull, exponential, lognormal, and gamma probability distributions (Kiefer, 1988). The two widely-used parametric distributions in the literature are the exponential distributions and the Weibull distributions (Dadi et al., 2004; Cho and White, 2010) used in this paper.

The parameters can be estimated by maximum likelihood and the log likelihood function can be expressed as:

$$\ln L(\theta) = \sum_{i=1}^{n} \left\{ d_{i \ln f}\left(t_{i,\theta}\right) + (1 - d_i) \ln S\left(t_{i,\theta}\right) \right\} \tag{7}$$

where $f(t_i, \theta)$ is the density function and θ is the parameter vector, d_i is a censoring indicator that takes the value 1 for households who have adopted and 0 for right-censored values. In addition to time itself, the distribution of adoption durations may be influenced by a number of other factors mentioned above. Let X be a vector of time-invariant covariates and β a vector of associated unknown parameters. Therefore, the hazard function can be reformulated to allow for the influence of explanatory variables as follows:

$$h(t, x, \theta, \beta) = h_0(t, \theta) exp(x'\beta). \tag{8}$$

Where the first term in the right side of the equation, $h_0(t, \theta)$, represents the baseline hazard and the second term is the relative hazard. To estimate the hazard function and the effect of explanatory variables on the hazard, a proportional hazard model, pioneered by (Cox, 1972), is applied in this paper. One of the most attractive features of the Cox Proportional Hazard model is that the baseline hazard need not be estimated. Additionally, the model does not impose any shape on the hazard function. It is only assumed that the hazard function is the same for each subject, and that given the covariates, the hazard between one subject and another differs only by a multiplicative constant. The signs of β are interpreted as the direction of the effect that the explanatory variables have on the conditional probability of completing a spell.

We therefore employ a duration model that incorporates a term for unobserved farm household heterogeneity. Given that no specific functional form for hazard rates exist, we employ a general class of models known as proportional-hazard models proposed by Cox.

4. Empirical results

4.1. Non-parametric results

In survival analysis, it is common practice to have some summary of the survival times of all the individuals in the sample. We employ a non-parametric approach called the Kaplan–Meier estimate of the survivor function if the data contains censored observations. It does not assume distribution of survival times for the survivor function (Kaplan and Meier, 1958). Such summaries are useful for suggesting appropriate functional forms for parametric analysis and for specification analysis of more complicated models (Kiefer, 1988). In technology adoption studies, they may also help by depicting the speed of adoption of different technologies and facilitating comparisons of individuals sampled from different populations. Here, since the data contains censored observations, the Kaplan–Meier method was used to summarize the length of time farmers waited before adopting the IMVs. Fig. 4 illustrates the relationship between the proportion of non-adopters and the adoption spell, which is the time between the first year of information obtained about the varieties and the adoption of the improved maize variety. It is clear that the survival rate falls quickly as time goes on. The rate of diffusion is not uniform over time. This means that the hazard rate increases as time increases. That is, the probability that a farmer will adopt, given that he or she has not adopted previously, seems to increase over time.

As clearly shown in Fig. 5 below, the diffusion of the IMVs was quite slow during 1970–1999, but then it increased, on average, more rapidly thereafter.

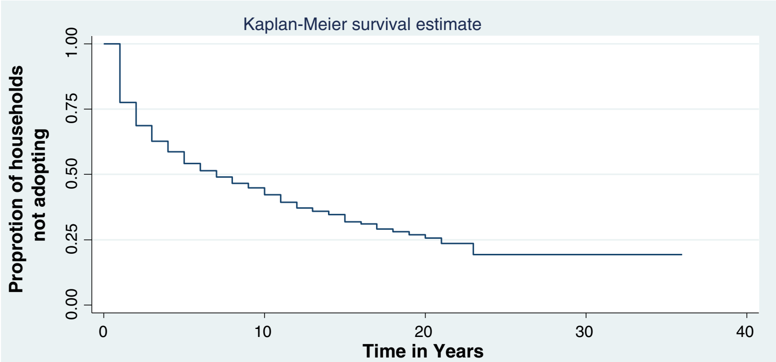

Fig. 4. Kaplan–Meier survival estimate.

4.2. Parametric results

The econometric model specifications for duration analysis are often based on exponential or Weibull distributions (Cho and White, 2010). The Akaike information criterion (AIC)[2] test statistics show that there is no significant difference between the distributions of the Weibull model and the exponential model (the AIC for the Weibull distribution is 2583.65 and the AIC for the exponential distribution is 2583.7). The results from Weibull and exponential models are qualitatively similar. Results are therefore discussed based on Weibull model but for comparison purposes results from the exponential model are also reported.

In estimating the models, unobserved heterogeneity (e.g. unobserved skills of the farmer) may arise due to functional form misspecification, omission of important variables, or misspecification of included variables; this often leads to inaccurate inferences about duration dependence and the effects of explanatory variables (Kiefer, 1988). In the presence of unobserved heterogeneity each individual with the same values of all covariates may have different hazards out of a given state. In such situations, the baseline hazard will pick up unobserved firm-specific heterogeneity and will cause a downward bias in the degree of duration dependence. The likelihood ratio test that there is no unobserved heterogeneity ($H_0 : \theta = 0$)) is rejected in both models (chibar2 (01) $= 67.98(0.000)^{***}$ and chibar2(01) $= 16.37(0.000)^{***}$ for Weibull and exponential models, respectively). This shows that unobserved heterogeneity is an important feature of adoption decisions, and it is therefore appropriate to employ a frailty model in order to capture unobserved heterogeneity in both models. Frailty models are essentially random effects duration models that account for unobserved heterogeneity (Gutierrez, 2002). The Weibull model with gamma frailty does not converge and thus we estimated the inverse Gaussian frailty model.

The regression results are shown in Table 2.[3] The data reject the hypothesis that the shape parameter $p = 1$ (or $\ln p = 0$). In our case, since p is greater than one, there is a positive duration dependence and the hazard is monotonically increasing — that is the observations are failing at a faster rate as time goes on. In other words, the rate of adoption is increasing. In standard duration models, which fail to account adequately for all the variability in the observed failure times, a hazard ratio is interpreted as a proportional shift in the hazard function corresponding to one unit change in the covariate. However, the hazard ratio in a frailty model carries this usual interpretation only if comparing two hazards conditional on a given α, which is unobservable multiplicative effect (Gutierrez, 2002). A hazard ratio greater than one indicates an increase in the hazard of failure (i.e. speed up adoption) while less than one, decrease the hazard (i.e. decrease in adoption).

Table 2 shows that many variables influence the speed of adoption of improved maize varieties.[4] Consistent with earlier studies (e.g., (Abdulai and Huffman, 2005; Kaliba et al., 2000)), the speed of adoption is faster for farmers whose main source of information about the varieties is government extension. Farmers who cited relatives as the main source of information have a 41.5% lower hazard rate than those whose extension agents as a main source of information, given the same value of frailty. This suggests that in view of the importance of maize in the Tanzanian economy, strengthening the role of extension workers to speed up the dissemination of varieties is important.

Unlike (Teklewold et al., 2013; Kassie et al., 2013), who used self-reported rainfall and plot-level crop-production disturbances, we used actual lagged rainfall data to understand the effect of rainfall on the dynamics of adoption of IMVs. The speed of adoption significantly increased with rainfall. Kaliba et al. (2000) found similar results in the analysis of the adoption of improved maize seeds and inorganic fertilizer for maize production in Tanzania. This implies that farmers in low rainfall areas are less likely to adopt improved seeds than farmers in high rainfall areas unless adoption of improved varieties is complemented with moisture conserving practices/technologies. The speed of adoption is also influenced by social capital variables, but with different signs and magnitudes. The number of grain traders that a respondent knows and farmers'

[2] The AIC is defined as AIC $= -2 \ln L + 2\,(k + c)$; where k is the number of independent variables, and c is the number of model-specific distribution parameters: it is one for the exponential distribution and two for the Weibull and Gompertz distribution.

[3] In our data we have multiple cases of adoption per farmer. This may lead to a correlation across the different varieties for a given household that may bias estimates. To address this shared frailty model was estimated but we found no basic difference with the findings estimated with frailty model. As noted by (Gutierrez, 2002), both the frailty and shared frailty models can be equivalent in certain situations. The estimation results are available up on request from the authors.

[4] Some of the household characteristics such as the number of livestock, land size and household size that may change over a long period were not found to be significant. However, to check robustness of results we re-estimated the model without including these variables. The qualitative results are quite similar to the case were these variables included. The results are available up on request from the authors.

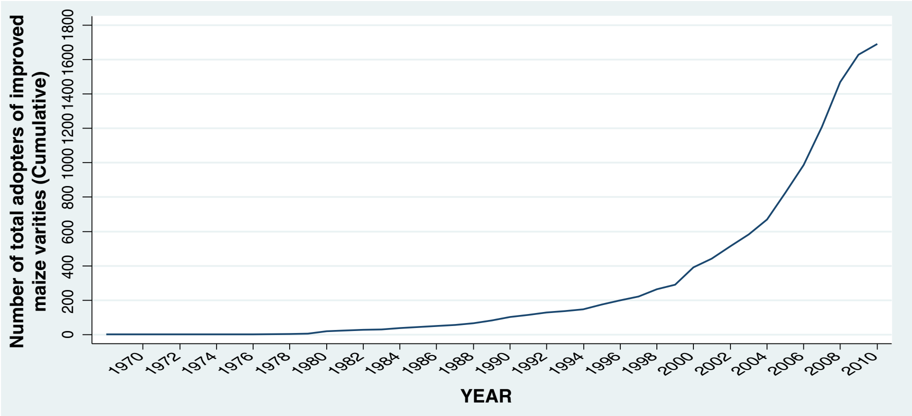

Fig. 5. The rate of adoption of IMVs over the study period (1970–2010).

group membership are positively related with the speed of adoption. All else equal, the hazard function for farmers with group membership is 1.32 times the hazard for farmers without group membership. However, we find that the number of relatives that the household can rely on in times of critical need is negatively related to the speed of adoption of the technology. This may support the hypothesis that social network may hinder the technology adoption process (Di Falco and Bulte, 2011).

Farmers' confidence in the skills of extension workers increases the speed of adoption. Improving the quality of the extension workers through, for example, upgrading their skills and increasing their acceptance by the farmers will speed up the adoption process.

Land quality as measured by soil fertility affects the speed of the adoption decision of farm households. Those households with good, fertile plots have more incentive to adopt a new variety, compared to those who have less fertile plots, because returns from adoption of IMVs is high on fertile soil. This is an important finding given the low level of fertilizer use (only 5% of sample households) in the study areas.

With respect to socio-demographic characteristics, the analysis shows that a one-year increase in age decreases the adoption hazard by almost 10%, perhaps because young farmers are stronger (so better able to provide the labor needed by productivity-enhancing technologies) and have longer planning horizons, and are thus less risk-averse. However, as a farmer gets older, the speed of adoption increases as shown by the estimate of age square, significant at 11%. This might be due to the knowledge accumulated over the years of their farming experiences. The regression results reveal that those with secondary-level and above education are significantly and negatively related to the speed of adoption. This is probably because these households might have better opportunities outside the farm and hence might be less interested in investing in agriculture. Alternatively as argued by Dadi et al. (2004), the use of improved maize technology in the study area may not be considered a complex technology that requires a high level of education. On the other hand, Abdulai and Huffman (2005) and Matuschke and Qaim (2008) found that an increase in the household head's years of schooling shortens the duration of non-adoption of pearl millet hybrids and crossbred-cow technology in rural India and Tanzania, respectively. As expected, the number of years the household has been living in its current village has a positive and significant effect on the speed of adoption; this is probably the effect of social capital. Targeting those farmers residing long in the village could be considered a good extension approach to speed the dissemination and adoption of technologies.

Finally, the results show that the speed of adoption is lower for farm households in Mbulu and Kilosa districts compared to households in Karatu. This may reveal the importance of geospatial differences including agro-ecology and infrastructure in the technology dissemination process.

5. Conclusion

This study examines the factors influencing the speed of adoption of improved maize varieties in rural Tanzania using duration models. The results, based on a survey data collected in two maize–legume farming systems in the eastern and northern zones of Tanzania, show that farmers who have more fertile land are more likely to adopt a new variety probably because the performance of technologies on good fertile soil is rewarding. The importance of rainfall in influencing the speed of adoption suggests the importance of introducing moisture conserving and water harvesting practices that can serve as a buffer against low rainfall.

Information acquired through government extension officers was found to be an important factor in speeding up technology adoption. This highlights the importance of strengthening extension services and improving the skill of extension officers in supplying quality information that minimizes the risk of adoption due to incomplete information transfer.

We find, as have others, that the speed of adoption increases with participation in farmers' group membership and with the number of grain traders that farmers know in their vicinity. These findings suggest that in the presence of multiple market failures, local rural institutions and service providers need to be supported because they effectively assist farmers in providing credit, inputs, information, and stable market outlets. The significance of government support during crop failure indicates the importance of introducing risk mitigation strategies to accelerate adoption of technologies.

The current study is based on cross-sectional data but adoption is a dynamic and ongoing process. From a future

Table 2
Estimates of duration models of improved maize varieties (IMVs) adoption.

Variables	Weibull	Exponential
Household characteristics		
Sex of the household head	0.808	0.855
	(0.197)	(0.147)
Age of the household head	0.901***	0.923***
	(0.025)	(0.019)
Age square of household head	1.000	1.000*
	(0.000)	(0.000)
Household head completed primary	0.888	0.884
	(0.228)	(0.167)
Household head completed secondary	0.418***	0.528***
	(0.094)	(0.087)
Household size	1.055	1.055*
	(0.046)	(0.034)
No. of years household lives in the village	1.027***	1.020***
	(0.006)	(0.004)
Land size	0.780	0.867
	(0.128)	(0.103)
Livestock owned	1.084	1.028
	(0.104)	(0.071)
Per capita expenditure	1.117	1.113
	(0.115)	(0.083)
Access to services		
Distance to the main market	0.909	0.950
	(0.091)	(0.067)
Distance to the nearest seed dealer	0.982	0.979
	(0.079)	(0.055)
Access to credit	1.132	1.119
	(0.232)	(0.167)
Information sources		
Main source of information: relatives	0.542***	0.662***
	(0.097)	(0.084)
Main source of information: friends/ neighbors	0.593***	0.706***
	(0.104)	(0.087)
Social capital and network and trust indicators		
Number of grain traders	1.023*	1.019*
	(0.013)	(0.010)
Membership in rural institutions/group	1.323*	1.242**
	(0.202)	(0.135)
Number of relatives in the village	0.944***	0.956***
	(0.017)	(0.013)
Government support during crop failure	1.399**	1.269**
	(0.217)	(0.138)
Confident with skills of extension workers	1.093*	1.073*
	(0.058)	(0.041)
Cultivated area good/medium fertility	1.740**	1.501**
	(0.402)	(0.254)
Village level variables		
Annual rainfall	2.580***	1.949***
	(0.274)	(0.141)
Mbulu district	0.663**	0.754**
	(0.133)	(0.107)
Mvomero district	0.759	0.764
	(0.196)	(0.142)
Kilosa district	0.522***	0.602***
	(0.124)	(0.105)
Constant	0.002***	0.004***
	(0.003)	(0.005)
P	1.607***	
	(0.086)	
θ	6.092***	0.321***
	(1.867)	(0.096)
Log likelihood	−1231.83	−1257.66

Note: coefficients are hazard ratios; *, **, and *** represent level of significance at 10, 5 and 1% level, respectively; figures in parenthesis are standard errors.

study perspective, it is important to collect data over time to understand the adoption process and capture the dynamics of some of the explanatory variables that influence the duration of adoption.

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