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Adoption Spells of Improved Potato Varieties by Smallholder Farmers in Eastern Ethiopia: The Duration Approach

Abstract. Potato is mainly tagged as a food security crop in Ethiopia. However, its productivity remains low due to low adoption of improved technologies by smallholder farmers. Duration models, namely, Parametric (Weibull) and Non-parametric (Kaplan Meier) were used to analyze the data gathered from 365 sample farmers. The Non-parametric result revealed that the average duration that potato growers should wait before adopting a new variety is about 3.5 years. The Weibull regression indicated that timely availability of seed, access to labor and irrigation water, land size, and adaptation strategy by farmers are found to be factors curtailing the timeframe to adopt improved potato varieties. The regression analysis revealed that costs of inputs such as manure and compost, environmental and market factors such as drought, pest and disease outbreaks, price variability of potato seed, and quality of potato seed were found to be factors influencing adoption decisions of improved potato varieties by smallholder farmers.

Key words: adoption spell, Weibull, static, potato varieties, Ethiopia

JEL Classification: Q16, O33

Introduction

Literature is replete on the economic importance of potato (*Solanum tuberosum L)* production. For instance, potato serves as a food security crop (Birch *et al*., 2012; Hirpa *et al*, 2010); it provides high yield quality product per unit of input with a shorter crop cycle (mostly less than 120 days)(Hirpa *et al.,* 2010; Abebe *et al*., 2013; Sanginga and Mbabu, 2015); it generates income and employment opportunity for the poor (Muthoni *et al*., 2010; Tesfaye *et al*., 2010; Abebe *et al*., 2013; Sanginga and Mbabu, 2015); it contributes to the economic sustainability of agricultural systems in developing countries (Thompson and Scoones,2009); it is relatively cheap but nutritionally rich (Sanginga and Mbabu, 2015); it is ideally suited to places where land is limited and labor is abundant (Muthoni *et al*., 2010); and it serves as both food and cash income in the densely populated highlands of sub-Saharan Africa (SSA) (Gildemacher *et al*., 2009). Although potato is an increasingly important food crop in developing countries, little attention has been given in the adoption literature, compared to other staple crops such as rice, maize, and sorghum (Abebe *et al*., 2013).

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As is in the case elsewhere in the world, potato is one of the main root crops grown by Ethiopian farmers. In Ethiopia, potato ranks first in the category of root and tuber crops in terms of area coverage and total production (Gebrehanna *et al*., 2018). According to the recent report of Central Statistics Authority (CSA), about 1.2 million farmers grow potato on 70, 131.32 hectares of land in Ethiopia (CSA, 2017) as food and cash crop during "Maher[5]" season. In Eastern Ethiopia, especially, potato is the second most important crop next to *khat*[6] (*Chata edulis Forsk*) in supporting farmers' livelihoods (Mulatu *et al*., 2005).

In spite of its critical importance to Ethiopian farmers, potato farming is characterized by decades of stagnation and volatility in production and productivity, though there has been an increase in total potato production over the years. The low production is partly attributed to limited usage of yield-enhancing technologies by smallholder farmers. For instances, empirical findings indicate that the current average yield level of 13.8 tone/ha (CSA, 2017) is far lower than that of many African countries such as Malawi (34 tone/ha), Egypt (24.8 tone/ha), and Morocco (24.2 tone/ha) (FAO, 2016). This could be more than tripled to about 30-40 tone/ha through a combination of different technologies.

Improved crop varieties can play multiple roles in improving farmers' livelihood. Among others, the oft-cited roles of improved crop verities are: They can ensure the availability of sufficient food for growing populations (Rizvi et al., 2012); they are meant to enhance yield (Abdulai and Huffman, 2005; Adekambi *et al.,* 2009; Sanchez *et al.,* 2009; Kassie *et al*., 2010; Solomon *et al*., 2010; Wanyama *et al.,* 2010; Abebe *et al*., 2013;Bekele, 2015; Beyene and Kassie, 2015; Lemessa, 2017; Zizinga *et al*., 2017); and they are drought-tolerant and disease-resistant (Abebe *et al*., 2013).

New technology adoption studies are proliferating and their importance has been profusely documented in economic literature (Croppenstedt *et al*., 2003; Dadi *et al.,* 2004; Dercon and Christiaensen, 2007; Hagos, 2003; Kassie *et al*., 2008; Kassie *et al*., 2009; Negatu and Parikh, 1999; Shiferaw and Holden, 1998; Teklewold *et al*., 2013; Abebe and Bekele, 2015; Abdulai and Huffman, 2005; Beyene and Kassie, 2015; Lemessa, 2017). Despite this, many studies on the adoption of new technologies, and the existing empirical and theoretical frameworks, tend to provide only a limited explanation on the adoption durations – commonly known as adoption spell – the time that farmers should wait before adopting a given technology once they have heard about the existence of the technology.

Empirical models of adoption studies in the past have frequently used choice models such as logit, tobit, probit or the combination of the three in static framework (Abdulai and Huffman, 2005; Abebe and Bekele, 2015; Lemessa, 2017; Abdulai *et al*., 2018). However, these models fail to address the effect of covariates on the time-path of adoption, which is an important attribute of the adoption process (Abdulai and Huffman, 2005). Though the static aspects of technology adoption explicate why, at a point of time, some farmers adopt and others did not, they fail to explain why some farmers are early and quick adopters, while others are late and slow adopters and others dis-adopt. Nor can they assess the impacts of time-varying factors such as output and input prices on adoption decisions of smallholder farmers (Abdulai and Huffman, 2005; Beyene and Kassie, 2015; Lemessa, 2017).

The scant empirical works on duration models of adoption decisions of new technologies in developing countries overly focuses on the cereals and the root crops

[5] Meher reefers to long rainy season from June to August in Ethiopia.
[6] Khat is an stimulant cash crop mainly grown in eastern Ethiopia.

sectors, which is forlorn. For instance, Dadi *et al.* (2004) used the duration model to analyze the adoption spell of teff; Abebe and Bekele (2015) used it to analyze the adoption of common beans; Beyene and Kassie (2015), Bekele (2015) and Lemessa (2017) used it to analyze the adoption spell of improved maize varieties.

Given the paucity of literature on adoption spells of root crops in general and Improved Potato Verities (IPVs) in particular, this study aims to thoroughly analyze the adoption spell of IPVs and its determinants in eastern Ethiopia. By using duration models to analyze the adoption spell of IPVs, the contributions of this study are pronged into three folds:

1. It contributes to the dearth of literature on the application of duration models to analyze the adoption spell of root crops in general and IPVs in particular. To the best of the authors' knowledge, this is the first study to apply such a model to the study of the adoption spell of IPVs as adoption spell differs across different crop types;
2. This study result also generates empirical knowledge on factors that speed-up and delay the adoption of IPVs in eastern Ethiopia.
3. By assessing factors that affect the adoption spell, this paper contributes to informing decision makers to design relevant agricultural policies to fortify and speed-up technology disseminations; particularly that of IPVs.

Data and analysis methods

Study setting

East Hararghe zone is located in the Oromia regional state of eastern Ethiopia. It is characterized by complex agro ecological areas, high population density, and high ratio of cash to food crops, rainfall variability, and high level of food insecurity (Tesfaye and Seifu, 2016). Jaleta and Gardebroek (2008) noted that 90.7% of the households in Haramaya district of eastern Hararghe grow potato at an average of 0.21 ha, with a maximum of 1 ha. The average area in ha is quite small, since farmers in this region are primarily subsistence farmers who combine potato production with that of other crops. Jaleta and Gardebroek (2008) also noted that the share of land allocated to potato production varies with farm size, i.e., as the farm size increases the share of land size allocated to potato production also increases. The livelihoods in this area are comprised of agro-pastoralists and pastoralists. There are 19 districts in the zone with 14 of them being agro-pastoralists. The rainfall is bimodal with the Kiremt rain being important in the crop-dependent areas. The amount of rainfall varies between 650 and 750 mm, while the average temperature of the districts varies between 25 and 30 °C (Mulugeta *et al*. 2018).

Method of sampling and data collections

This study was conducted in three districts of eastern Hararghe Zone, namely: Haramaya, Kombolcha and Kersa. The three districts were selected purposively because of their high potential production coverage. The study used primary data gathered through a cross-sectional survey to achieve the predefined objectives. A multi-level mixed sampling technique was used to determine sample households and collect the data. First, sample districts that have high potato production coverage were selected purposively. Second, sample kebeles[7] from these districts were selected purposively with high potato production potential. Accordingly, five kebeles from Haramya district and three from both Kombolcha and Kersa districts selected. Finally, the sampled households were selected using systematic sampling. A considerable sample size (365 smallholder farmers who adopted IPVs) was used to make the sample more representative. The data were collected from farm households using a structured questionnaire, which were distributed and collected by enumerators who know the culture and language of the study area. In order to triangulate the survey data and deepen our knowledge on the adoption spell of IPVs adoption, Focus Group Discussions (FGDs) were organized with model farmers.

Both descriptive (means, graphs, ratios, figures) and econometric methods of data analysis were used to achieve the stated objectives. Particularly, a duration analytical model was employed to determine the time that farmers need to wait before adopting IPVs and the factors that affect the adoption spell.

Econometric specification of duration model

The Duration Analysis (DA) is a statistical method originated from biometrics and statistical engineering that studies the expected time an individual spends in one state before transitioning to another. DA is dichotomous choice methods, in which individual adoption decisions are modelled using cross-sectional data and measurements of aggregate diffusion in a dynamic framework (Alcon *et al*., 2011; Murage *et al*., 2011). Originally, as it dealt with the transition process of death of a patient, or mechanical failure of a piece of equipment, it has acquired the name “survival analyses” (Alcon *et al*., 2011). Recently (Fuglie and Kascak, 2001; M. Burton *et al*., 2003; Dadi *et al*., 2004; Abdulai and Huffman, 2005; Matuschke and Qaim, 2008, Butler and Moser, 2010, and Beyene and Kassie, 2015; Lemessa, 2017) it has been used to capture the dynamic aspects of new technology adoption processes. The particular cases where duration analysis has been applied is in adoption of agricultural technologies for improved maize, potato, common bean varieties, etc.

As an example, Fuglie and Kascak (2001) used the duration model and estimated the long-term trends in adoption and diffusion of conservation tillage by U.S. farmers. Burton *et al*. (2003) explored the determinants of adoption of organic horticultural crops in the UK; and Dadi *et al*. (2004) estimated the impact of variables on the timing of agricultural technology adoption by smallholders in Ethiopia. Abdulai and Huffman (2005) explained the diffusion and farmer’s adoption of crossbred-cow technologies in Tanzania. D’Emden *et al*. (2006) also investigated significant variables on the soil-conserving adoption by grain farmers in Australia. Matuschke and Qaim (2008) and Beyene and Kassie (2015) studied the dynamics of hybrid pearl and improved maize varieties adoption in India and Tanzania, respectively.

In duration analysis, the concept of probability plays a fundamental role (Alcon *et al*., 2011; Abdulai and Huffman, 2005; Beyene and Kassie, 2015). This means, instead of focusing on the time length of a spell, one can consider the probability of its end, or on the probability of transition to a new state. In a technology adoption study, the important question would be therefore: what is the probability of a farmer adopting a certain technology at time *t*, given it has not been adopted by that time (Beyene and Kassie, 2015;

[7] Kebele is the smallest administrative unit in Ethiopia.

Burton *et al*., 2003). To answer this question, the hazard function is used, which is explained below.

Firstly, to derive the hazard function, we consider a given household; define **T**[8] as "**failure**" time. This is a time at which the household makes a transition from non-adoption to adoption state. Secondly, T is a non-negative continuous random variable representing the duration of stay in a given state – in this case adoption of IPVs, the time a farmer waits before adopting IPVs. This waiting time is commonly known as "adoption spell". Finally, we explained the cumulative distribution function (CDF) of T as follows:

$$F(T) = \int_t^0 f(x)d_x = P(T \leq t)\ t \geq 0 \tag{1}$$

The above equation indicates that the probability that duration time in this case T is smaller or equal to some value *t*. Following the CDF, the probability density function of (Pdf) for T is the first partial derivate of the CDF with respect to time *t*.

$$f(t) = \frac{\partial F(t)}{\partial t} \tag{2}$$

The hazard function can be thought of as the continuous time version of a sequence of conditional probabilities (in this case, conditional probabilities of IPVs adoption). The cumulative distribution, survivor and hazard functions are equivalent ways of expressing the distribution of T. Therefore, the survival function in the case of a farmer waiting before adoption of a given technology is the probability of an individual not adopting until or beyond time *t*, defined as:

$$S(t) = P_r(T \geq t) = 1 - F(t) = \int_t^\infty f(x)dx \tag{3}$$

The DA centers on a hazard function with the numerator as a conditional probability that the event will occur in the interval $t, t + td$ given that it has not occurred before, and the denominator is the width of the interval $T \geq t$

$$= P(t \leq T \leq t + dt/T \geq t) \tag{4}$$

Since our objective is to determine the average waiting time before farmers adopt IPVS, we computed the average probability of leaving the state per unit of time period over a short time interval, at or after *t* as follows:

$$h(t) = \lim_{\Delta t \to \infty} P_r\,(t \leq T < +t + dt/T \geq t) = \lim_{\Delta t \to \infty} \frac{f(t)}{1 - F(t)} \tag{5}$$

The hazard function can be derived from equation (5) in the following ways:

$$h(t) = \frac{\lim_{dt \to 0} P(t \leq T < t + dt/T \geq t)}{dt} \tag{6}$$

$$= \frac{\lim_{dt \to 0} P(T \geq t\ /t < T \leq t + dt)P(t < T \leq t + dt)}{P(T \geq t)dt} \tag{7}$$

$$= \frac{\lim_{dt \to 0} P(T \geq t\ /t < T \leq t + dt)f(x)}{S(t)dt} \tag{8}$$

1. Not that a failure time (**T**) in this case is defined as a qualitative variable making an end-point, that means, there is no negative connotations attached to the term failure for this study purpose.

But $\lim_{dt \to 0} P(T \geq t\ /t < T \leq t + dt) = 1$

$$h(t) = \frac{f(x)}{1-F(T)} \tag{9}$$

$$= \frac{dS(t)}{dt} = \frac{d(1-F(t)}{dt} = \frac{-d(F(t)}{dt} = -f(t) \tag{10}$$

$$= \frac{-dlog(s(t))}{dt} = \frac{-dS(t)}{\frac{dt}{S(t)}} = \frac{f(t)}{S(t)} = h(t) \tag{11}$$

$$\text{Therefore } h(t) = \frac{f(t)}{S(t)} \tag{12}$$

Where *F(t)* and *f(t)* are the corresponding cumulative distribution and probability density functions. In this study, the hazard function represents the probability that a farmer adopts IPVs at time *(t)* given that he or she has not adopted before *(t)*.

Specification of parametric and non-parametric models in duration analysis

Duration models use different parametric and non-parametric functional forms (Lemessa, 2017). Kaplan-Meire and Log-rank test are among the non-parametric functional forms. On the other hand, Weibull, Gompertz, logistic, lognormal, loglogistic and exponential distributions are among the parametric forms (Cleves *et al.*, 2004). Parametric models are more efficient for data usage. This is because they do not reject what happens to covariates where adoptions occur (Lemessa, 2017). Among parametric distributions, the two most commonly used are the exponential and Weibull distributions. Given this fact, we used these functional forms of DA to identify factors that affect the durations of IPVs adoption. Kaplan-Meire survival estimate of non-parametric forms is used for the estimation of the survival time for comparison purpose.

Before being directly used in their CDF from, the hazard functional form of these distributions should be computed for analysis purpose. The hazard for the exponential distribution is a constant, meaning that the conditional probability of failure or change of state, in a given short interval does not depend on duration. For this reason, it is called 'memory less', that is, the passage of time does not affect its value (Burton *et al*., 2003).

This 'memory-less-constant' hazard function is characterized by no duration dependence, $h(t) = \lambda$ where the parameter $\lambda > 0$ implies that the passage of time does not influence the hazard rate. The exponential CDF, pdf and its hazard functional form is given as follows:

$$F(t) = 1 - exp^{(-\beta t)} \tag{13}$$

$$S(t) = 1 - \left(1 - exp^{(-\beta t)}\right) = exp^{(-\beta t)} \tag{14}$$

$$f(t) = \frac{\partial F(t)}{\partial t} = \beta exp^{(-\beta t)} \tag{15}$$

$$h(t) = \frac{f(t)}{S(t)} = \frac{\beta exp^{(-\beta t)}}{exp^{(-\beta t)}} = \beta \tag{16}$$

Where β is the only ancillary parameter to be estimated. The result of this model is the expected remaining time to adopt and is independent of prior survival times. The CDF, pdf and hazard functional form of Weibull is given as follows:

$$F(t) = 1 - exp^{-(}\beta t^{\alpha}) \tag{17}$$

$$S(t) = 1 - \left(1 - exp^{-(}\beta t^{\alpha}\right) = exp^{-(}\beta t^{\alpha}) \tag{18}$$

$$h(t) = \frac{f(t)}{S(t)} = \beta \alpha t^{\alpha - 1} \tag{19}$$

The interpretation of the coefficients is made from the magnitude of α. $If\ \alpha > 1,$ it shows increasing hazard, $\alpha < 1,$ indicates decreasing hazard and if $\alpha = 1$ it shows a constant hazard which is an exponential function.

Result and Discussion

Socioeconomic characteristics of the sample households

The farm and household characteristics of respondents are presented in Table 1. The socioeconomic distribution of farm households shows that the average age of respondents was 35 years with 3.4 mean years of schooling and average family size of 6 members. Land holding of farm households was very small, averaging about 0.35 ha per household. The minimum and maximum land holdings were found to be 0 (rented land only) and 3 ha, respectively. The main job in the study area is farming: 70% of respondents do not have additional employment to complement their livelihood. Potato production in the study area is male-dominated (98%).

Table 1. Socioeconomic characteristics of potato growers (N=365)

Variables	Unit of measurement	Mean	Std. Dev.	Min	Max
Year gap (dependent variable)	Measured in years	3.45	2.230585	0	18
Family size	Measured in numbers	6.17	3.021656	0	16
Sex	Dummy variable	.99	.1042525	0	1
Age	Measured in years	35.88	11.2253	15	77
Education level	Measured in years of schooling	3.41	3.739585	0	15
Additional employment	Dummy variable	.31	.9048351	0	11
Land size	Measured in Hectares	.35	.3942921	0	3
Transportation access	Dummy variable	.73	1.190787	0	11
Distance to the nearest market	Measured in minutes	46.89	53.27052	0	900
Distance to center market	Measured in minutes	73.74	70.82293	0	600
Distance to potato plot	Measured in minutes	15.74	12.19868	0	90

Source: Own computations from the survey data, 2017.

Regarding distances to different information centers, the descriptive statistics show that potato growers walk on average 46.8 minutes to the nearest market center, 73.7 minutes to the main market, and 15.7 minutes to their potato plot.

Types of potato varieties aware/known to the farmers

There were numerous types of IPVs known by the potato growers over the spanning period of 1987-2017 (the study period). Figure 1 shows the percentage distributions of

IPVs. Accordingly, Shantam is found to be the most popular types of IPVs (39.34%) followed by Ilillii Dima (18.56%), and Bubbu (13.86). From the sampled IPVs Gudanne is found to be the least popular (5.54%) types IPVs.

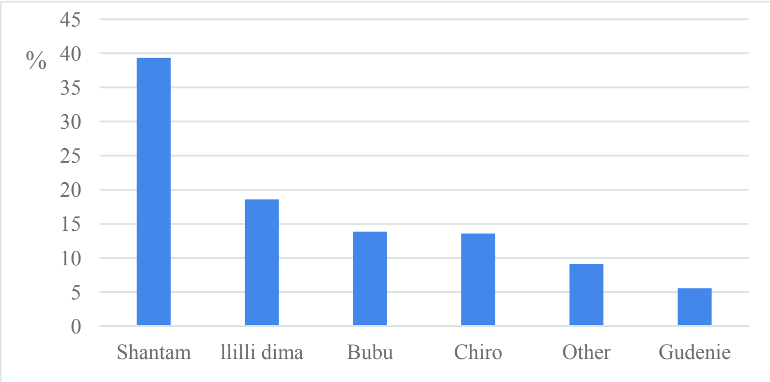

Fig. 1. Types of Potato Varieties known by framers

Source: Authors' own calculations.

Table 2. Adoption spells of improved potato varieties

Year gap	Frequency	Percentage	Cum.
0	1	0.27	0.27
1	32	8.79	9.07
2	118	32.42	41.48
3	84	23.08	64.56
4	53	14.56	79.12
5	26	7.14	86.26
6	19	5.22	91.48
7	10	2.75	94.23
8	7	1.92	96.15
9	3	0.82	96.98
10	3	0.82	97.80
11	5	1.37	99.18
12	2	0.55	99.73
18	1	0.27	100.00

Source: Own computations from the survey data, 2017.

Despite the importance of high-yield technologies in addressing food security, farmers show high interest in the local potato varieties (LPVs) and we surmise that there would be high probability of dis-adopting the new technologies. In the focus group discussions

(FGD) organized with model farmers, they explained that they prefer LPVs like *Mogor*[9]to the IPVs. The reason raised during the FGD was (i) shallow knowledge about the IPVs, and incomplete package of the IPVs and complementary inputs, (ii) short shelf-life of IPVs as compared with LPVs, (iii) high exposure to pest and disease, wilt incidence, decaying and weight loss, and (iv) low crop aftermath of IPVs as compared with LPVs which is important for animal feeding in the study area.

Adoption gap/time farmers waited before adopting improved potato varieties

Adoption spell – the length of time farmers waited before adopting IPVs – is the time difference between the years they heard/knew about IPVs and the first time they started practicing the technology; in our case plantation of IPVs. The period spanning from 1987 (being the first year for the release of the IPVs) to 2017(being the year that this survey was conducted) was considered for the analysis of this study. The average adoption spell or the mean time in years that farmers waited before adopting IPVs over these periods was found to be about 3.5 years. The minimum and maximum waiting years before adopting IPVs were 0 and 18 respectively.

The results of duration analysis

Results of non-parametric (Kaplan Meier) duration

The non-parametric (Kaplan Meier) estimation of the survival function as described in Figure 2 was used for comparison purposes. The results of Kaplan-Meier estimates were reported because it does not assume distribution of survival times for the survivor function (Kaplan and Meier, 1958, Abebe and Kassie, 2015: Lemessa, 2017). On the other hand, for its simplicity, Kaplan Meier is more preferable for summaries in order to facilitate comparison between individuals, and to suggest an appropriate functional form for parametric analysis. Above all, it is used for specification analysis of more complicated models (Kiefer, 1988; Abebe and Kassie, 2015).

In Figure 2, the horizontal axis shows the number of years that elapsed before farmers adopted IPVs, whilst the vertical line shows the probability to adopt IPVs. The gap shows the difference between the years that farmers first got information (1987) about IPVs to the year that they planted or practiced IPVs on their plot. In this study, 1987 was conceived as the year that IPVs were released for the first time in Ethiopia.

Akin to a result obtained by Lemssa (2017) and Beyene and Kassie (2015), the result of this study demonstrates that the speed of adoption of IPVs was rapid in the early years and the survival rate falls quickly as time goes on, i.e. adoption become more sluggish and limited. In other words, hazard rate increases as time increases. Initially, when $t = 0$, the value of the survival functions was found to be exactly 1. This is because at the begining farmers are conceived to be conventional at that point. The value of survival function then continued to fall drastically in the first interval.

The non-parametric result of this study corroborates with the findings of: Abebe and Kassie (2015), who conducted a study on speed of adoption of improved maize varieties in Tanzania and found that the survival rate falls quickly as time goes on; Odendo *et al*.

[9] Mogor is one of the local potato varieties grown in Eastern Ethiopia, mainly Gurawa district (source: FGD).

(2010) who conducted a study on adoption of soil fertility enhancing technologies in western Kenya; Dadi *et al*. (2004) who conducted research on duration analysis of technological adoption in Ethiopian agriculture; and with Abdulai and Huffman (2005) who conducted work on the diffusion of new agricultural technologies in the case of crossbred-cow technology in Tanzania. On the other hand, from the smoothed adoption curve below (see Figure 3), it can be observed that adoption was swift at the earlier time, decreased to about 30 years and rose up again after about 35 years.

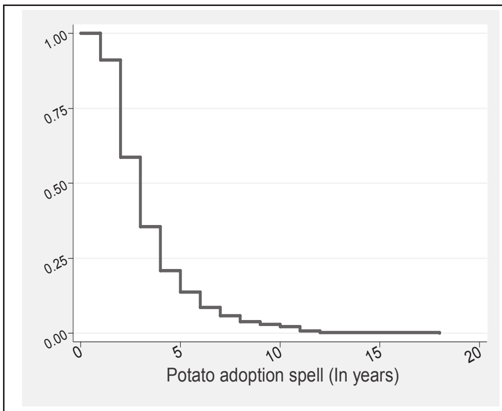

Fig. 2. Kaplan Meier estimate

Source: Authors' own calculations.

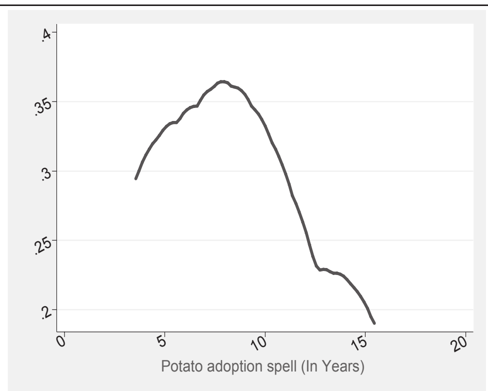

Fig. 3. Smoothed Kaplan Meier estimate

Source: Authors' own calculations.

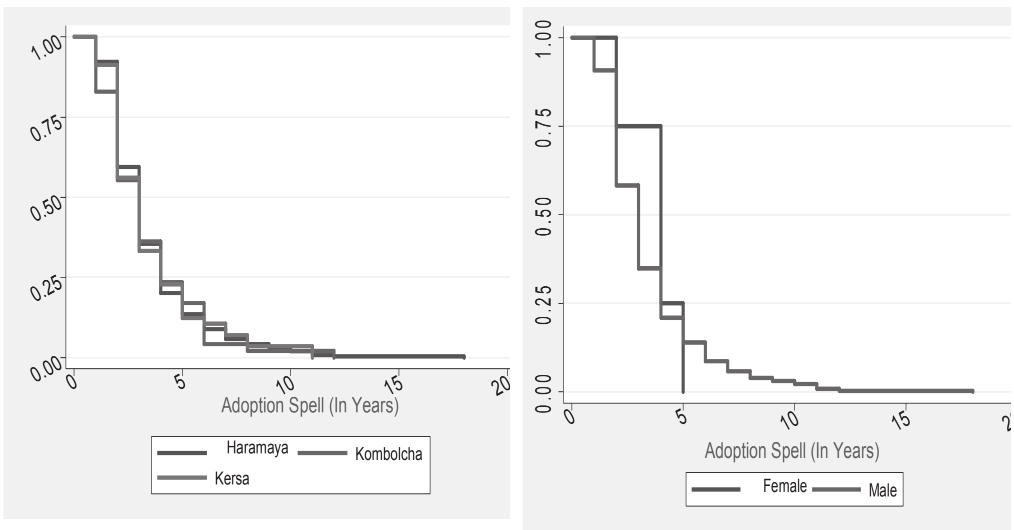

Fig. 4. Kaplan Meier estimate with regard to district and gender, respectively

Source: Authors' own calculations.

Figure 4 depicts the Kaplan Meier estimator of the survival function disaggregated by the three districts considered in this study. According to the comparison shown by the graph, farmer's speed of adoption in Haramaya district in the first five years after exposure to IPVs was very quick, followed by Kersa and Kombolcha. Farmers in Haramaya district are early adopters. We surmise that this could be due to the location of Haramaya district which is around the vicinity of Haramaya University, where consultation and different trainings are mainly exercised. Sex of the household was found to be one of the factors affecting the adoption spell of IPVs. In line with Abebe and Bekele (2015) and in contrary with Murage *et al*. (2011), female-headed households were found to be indeterminate to adopt IPVs as compared to their male counterparts. This situation is common in many developing countries like Ethiopia, where males spend more time in farming than their female counterparts. This implies the need for the design of gender-oriented technology promotion strategies.

Results of parametric analysis

The appropriateness of the fitted models is examined through various diagnostic methods for model specification. The primary diagnostics are based on the results of the Akaike's Information Criterion (AIC) [10]and the Bayesian Information Criterion (BIC).[11]The comparison of the two models using Akaike Information Criterion (AIC) revealed that the Weibull model fits the data better as shown by the lowest AIC (AIC = 3040.496) and Bayesian Information Criterion (BIC=3308.474). The AIC and BIC for exponential parametric functional form is 3151.806 and 3414.817, respectively, which is bigger as compared with that of Weibull. Hence, the Weibull model is adopted for data analysis in this study.

More importantly, the coefficients provided by the Weibull regression convey important messages about the underlying duration distribution (Shiferaw, 2006, Lemessa, 2017). Therefore, we report the coefficients of the estimates of the parameter, rather than the hazard ratio as it clearly shows the relationship between the covariates and the durations to adopt IPVs. The effects of the variables included in the model are interpreted using the Weibull regression coefficients. As was indicated in the methodology section of this study, whenever the derivative of the duration model with respect to time is greater than zero, which gives positive coefficient ($\beta > 0$), it indicates a longer pre-adoption spell, and lower probability of adoption, and positive duration dependence. With positive durations, the farmers should wait more time before adopting IPVs. If the derivative with respect to time is less than zero, which gives negative coefficients ($\beta < 0$), there is a negative duration dependence. A negative coefficient generally reflects a shorter pre-adoption spell and increase in the probability of adoption (Abdulai and Huffman, 2005; Abebe and Bekele, 2015, Lemessa, 2017). On the other hand, the variables do not have significant impact on the waiting time of IPVs adoption if the derivative is zero ($\beta = 0$).

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[10] $AIC = -2\ln(likelihood + 2(K + C)$,Where K is the number of independent variables, C is the number of model-specific distribution parameters (=1 for exponential and = 2 for Weibull distribution).

[8]$BIC = -2\ln(likelihood) + lnN * K$, where N is number of observations.

Table 3. Weibull regression results

_t	Robust Coef.	Std. Err.	z	P>z
Sex	.8721137	.4691933	1.86	0.063
Ethnicity	.42285	.0377502	11.20	0.000
Family size	-.0388196	.0191043	-2.03	0.042
Age	.0130928	.00534	2.45	0.014
Education	.0205689	.0121722	1.69	0.091
Manure cost	.0001546	.0000685	2.26	0.024
Compost cost	.2373445	.0850912	2.79	0.005
Timely availability of seed	-.2611179	.1132906	-2.30	0.021
Price variability of seed	.3823645	.1151254	3.32	0.001
Seed quality	.0615169	.0490395	1.25	0.210
Timely availability of fert	.0200819	.1254706	0.16	0.873
Price variability fert	-.2073682	.1787584	-1.16	0.246
Output information	.196973	.0961734	2.05	0.041
Access to labor	-.0758796	.0879125	-0.86	0.388
Irrigation access	-.0274644	.0845613	-0.32	0.745
Family labor	.0090311	.0056228	1.61	0.108
Hired labor	.0156075	.0052158	2.99	0.003
Land size	-.1674343	.1048675	-1.60	0.110
Distance to market	-.0012636	.0006544	-1.93	**0.054**
Pest disease	.0557844	.1075733	0.52	0.604
Drought	.0196624	.1662058	0.12	0.906
Adaptation strategy	-.0531386	.0340988	-1.56	0.119
_cons	-1.797899	.6033325	-2.98	0.003
/ln_p	2.184244	.0834198	26.18	0.000
p	8.88393	.7410954		7.543937
1/p	.1125628	.00939		.0955846

Source: Own computations from the survey data, 2017.

The estimated Weibull regression model result (Table 3) shows statistically significant coefficients for 12 out of the 22 variables included in the model. Among the socio-demographic factors, congruent to the study by Beyene and Kassie (2015), and in contrary with Abdulai and Huffman (2005) and Djokoto *et al*. (2016), the analysis of this study shows that age related to the durations of IPVs adoption, positively and significantly. This implies that younger farmers wait less time to adopt IPVs than old farmers. Young farmers are stronger (so they are better and able to provide the labor needed by productivity-enhancing technologies) and have longer planning horizons. Due to this reason they are less risk-averse (Beyene and Kassie, 2015) to ply new technologies.

The Weibull regression result shows that family size significantly curtails the durations to adopt IPVs. This means households with higher family size take less time to adopt IPVs. This is mainly because smallholder farmers with large family size can provide the necessary labor input which is highly required to make the technology more productive, on one hand. On the other hand, we surmise that households with larger family size might not have any alternative to sustain their family other than adopting the technology.

In contrary to some technology adoption studies (Abdulai and Huffman, 2005; Murage *et al*., 2011; Abebe and Bekele, 2015; Lemessa, 2017) and incongruent to others (Dadi *et al*., 2004; Beyene and Kassie, 2015), education level and availability of information are found to increase the duration of IPVs adoption. This is mainly due to either farmers with higher education and information waiting more time to adopt as they calculate the cost benefit of the technology, or educated households might have better opportunities outside the farm and hence might be less interested in investing in agriculture. Education and availability of information may also incentivize farmers to estimate the feasibility (shelf-life for example) of IPVs and they may have found that the IPVs are not worthwhile as compared with that of LPVs.

The Weibull regression model also revealed that timely availability of seed, distance to the nearest market, access to labor, access to irrigation, land size and adaptation strategy by farmers are found to be factors curtailing the durations to adopt IPVs. The negative and significant coefficient of distance to the nearest market shows that households closer to markets are more likely to adopt agricultural technologies than their counter-parts located in isolated areas.

The regression results also revealed that input costs such as manure and compost are found to significantly increase the waiting time of the IPVs adoption. Above all, environmental and market factors such as drought, pest and disease outbreak, price variability of potato seed, and seed quality problems are found to be factors which reduces the speed of the IPVs adoption decisions of farmers.

Conclusion and practical implication

This study analyzed the adoption spell that potato growers in eastern Ethiopia need to wait before adopting IPVs, and examined the important factors that affect their reluctance of adopting the IPVs as early as possible. Primary data were collected from 365 randomly selected farmers in three districts of eastern Ethiopia, namely: Haramaya, Kombolcha and Kersa. The mixture of duration models – non-parametric (Kaplan and Meier) and Parametric (Weibull) – were used to analyze the data.

The non-parametric result shows that the speed of IPVs adoption was high in the early years and falls as time goes on. It also shows that farmers on average need to wait about 3.5 years before adopting the IPVs. The descriptive results of the study showed that Shantam is the most popular type of IPVs adopted by farmers in the study area, followed by Ililli, Diima and Bubbu, respectively.

The regression results revealed that while variables such as age, education, input costs and output information affect the adoption spell of farmers positively, and prolong the time to adopt IPVs, other variables such as family size and distance to the nearest market affects the adoption spell negatively and curtail farmers' waiting time to adopt IPVs.

The main result of this study is that farmers' educational level and availability of output information are found to increase the duration of IPVs adoption. This is mainly due to either farmers with higher education and information waiting longer to adopt as they calculate the cost benefit of the technology, or educated households might have better opportunities outside the farm and hence might be less interested in investing in agriculture.

There are important implications that can be drawn from the findings for policy making. Firstly, full/complete packages of improved technologies should be provided to smallholder framers in order to boost yields of different crops. Secondly, the positive relationships between adoption of IPVs on the one hand and pest, diseases, and drought on the other suggests that adaptation strategies, or related policies, should be adopted and implemented in order to reduce the risk of agricultural impeding factors (climate and non-climate factors).Thirdly, gender mainstreaming programs (training, experience sharing, farm visits, etc.) should be designed and implemented to build the capacities of female farmers to make them more proactive. Fourthly, the positive relationship between adoption spell of IPVs, and education and information indicates that concerned parties should establish reliable information centers that the farmers can rely on. Fifthly, training programs on modern varieties of potato and its associated technology need to be increased through different stakeholders to promote the adoption of IPVs. This may help to harness more benefit from existing cropping systems in eastern Ethiopia where potato is one of the important crops.

Overall, knowing the average waiting time (in years) that the smallholder farmers need to wait before adopting IPVs is quite useful for policymakers to craft intervention strategies that may shorten the longer time that farmers wait to adopt the IPVs.

The following suggestions for further studies can also be drawn from this study. Firstly, better data sets (panel data) should be used to better understand and capture the dynamic nature of some of the explanatory variables and their effects on the adoption spell of IPVs. Secondly, for better comparison purposes and more meaningful to the average waiting time in future, future studies that cover cross-region or country should be conducted. Thirdly, the impact of IPVs adoption on household food security and livelihoods should be undertaken in a dynamic framework that takes adoption spell into account.

Finally, in Ethiopia, since agro-ecology (altitude, temperature and rainfall) highly affects production of potatoes, future studies should focus on the inclusion of this important variable.

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