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Assessing the speed of improved postharvest technology adoption in Tanzania: The role of social learning and agricultural extension services

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A B S T R A C T

The Purdue Improved Crop Storage (PICS) bag is often associated with preventing grain damage from insect infestation, reducing aflatoxin accumulation in stored grain, and avoiding exposure to hazardous storage chemicals. However, limited knowledge is available on the information channels driving the adoption of the technology. Using data from 429 households, this study examines the impacts of social learning and extension services on the speed of adoption of PICS bags in Tanzania. We utilized the doubly robust multivalued inverse probability weighted regression (MIPWRA) model to estimate the impact and the Laplace regression model to evaluate the heterogeneous effects of the two information channels. The impact results indicate that social learning and extension services reduce the time to adopt PICS bags by 51 % and 49 %, respectively. Moreover, the speed at which farmers adopted the technology was faster when using the two information channels jointly (61 %) than individually. The Laplace regression model results show that the marginal impacts of the two channels are higher for the households in the upper quantiles of the distribution, compared to the lower quantiles representing the early adopters. Designing policies that account for different adopter groups (innovators, early adopters, early majority, late majority, and laggards) is therefore essential.

1. Introduction

In Eastern and Southern Africa, it is estimated that postharvest grain losses (hereafter referred to as PHLs) amount to about US$1.6 billion per year, equivalent to 13.5 % of the total value of grain production predicted to be worth $11 billion (World Bank, 2011). Although these losses can occur at different stages of the post-production chain, most occur during storage, mainly due to pest (insects/rodents) damage, spillage, spoilage, and contaminations (Affognon et al., 2015; Abass et al., 2014). Pest infestations and poor quality of storage facilities are responsible for most of the total postharvest losses in Tanzania (World Bank, 2011). These losses reduce the quantities available for sale and future consumption, coupled with income loss through price discounts for damaged crop produce for most smallholder farmers (Kadjo et al., 2016). Qualitative postharvest losses can also lead to a loss in market prospects and nutritional value, leading to severe health risks if associated with the consumption of aflatoxin-contaminated grain (World Bank, 2011).

Most cereals, pulses, and oilseeds, such as maize, beans, and groundnuts, which form the base for food, income, and nutrition for most households in Tanzania, are highly vulnerable to aflatoxin contamination and insect damage. The postharvest loss is estimated at 30–40 % for cereals and even higher for perishable crops (URT/MOA, 2019). Notwithstanding the significant variations in the estimates, postharvest losses are estimated at over 20 % for the major cereals and pulses (Abass et al., 2014; Mutungi and Affognon, 2013; Abass et al., 2018). Farmers lose 11.7 % of their maize during harvesting activities, with about two-thirds occurring during storage (Chegere, 2018)

The primary loss agent for stored maize is the infestation by insects' such as the larger grain borer (LGB) and the maize weevils (Vowotor

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et al., 2005), while the significant pests for pulses such as beans are bruchids (Mutungi et al., 2020). PHLs should not only be viewed as the loss of solid matter and quality that pose food insecurity and food safety risks but also as the loss of all the resources (land, labor, capital) used in grain production (Sheahan and Barrett, 2017). Traditional storage structures commonly used by farmers (e.g., polypropylene bags, granaries made of plant materials, and mud) are not very effective in preventing insect infestations (Chigoverah and Mvumi, 2016; Abass et al., 2014; Omotilewa et al., 2019). Some farmers use grain protectants, including traditional admixtures (ash, soil, inert dust, plant oils, and other botanicals) and synthetic insecticides. Still, these suffer from limited efficacy, poor standardization and labeling, expiration, and adulteration, which may make them ineffective and dangerous to the health of consumers and the environment (World Bank, 2011).

Given the food security, food safety, economic and ecological implications of PHL reduction, it is critical to employ appropriate technologies at different stages of the post-production chain. Scaling the adoption of improved postharvest storage technologies (IPHTs) is one of the priority investment areas for commodity value chain development in Tanzania's Agricultural Sector Development Program (ASDP-II) (2016/2017–2025/2026). To this end, the Ministry of Agriculture (MOA) has recently adopted a 10-year National Postharvest Management Strategy (NPHMS) (2019–2029). The strategy entails promoting the availability, accessibility, affordability, and adoption of IPHTs.

Adopting IPHTs offers a potential solution to some of these problems. Recent studies show that airtight containers such as metal silos and PICS bags significantly reduce grain damage caused by insect infestation.[1] A study by Njoroge et al. (2014) showed that maize grain damage stored in airtight bags was lower (3.4 %) than in polypropylene bags (74 %) in the presence of LGB infestation. Similarly, the adoption of metal silos almost wholly eliminated the losses caused by insect pests, making it possible for farmers to save an average of 150–200 kg of maize grain annually in Kenya (Gitonga et al., 2013). Apart from preventing grain damage from insect infestation, hermetic bags reduce aflatoxin accumulation in stored grain (Ng'ang'a et al., 2016) and avoid exposure to hazardous synthetic insecticides. Among IPHTs, PICS bags, have received significant popularity among smallholder farmers in Tanzania. The increasing popularity of PICS bags can be ascribed to their efficacy in preventing grain damage from insect infestation, reducing aflatoxin accumulation in stored grain, and avoiding exposure to hazardous storage chemicals. Despite their positive effects, there is limited empirical evidence on the information channels driving its adoption in Tanzania. The empirical literature on agricultural technology adoption continues to ignore its dynamics (Montes de Oca Munguia et al., 2021). Considering adoption as a one-off static decision, many studies (e.g., Baoua et al., 2014; Chigoverah and Mvumi, 2016; Sudini et al., 2015) assessed the effectiveness of airtight storage containers in reducing PHLs based on ex-ante data and on-station experiments. However, technology adoption is not a one-off static decision but a dynamic process that entails information gathering and learning (Jabbar, 1998). Farmers move through several stages, from learning to adoption to continuous or discontinuous use over time (Rogers, 2003). The few existing ex-post studies (Gitonga et al., 2013; Tesfaye and Tirivayi, 2018) on IPHTs have assessed the extensive margin and did not consider the dynamic nature of technology adoption at the intensive margin. As such, rigorous studies on the speed of IPHT adoption remain rare in Tanzania.

Understanding the diffusion of modern technology depends on understanding the dynamic and cross-sectional patterns of technology adoption (Maertens and Barrett, 2013). This article contributes to filling this research gap by examining the determinants of the time to adopt PICS bags in Tanzania. Since PICS bags are relatively new and the uncertainties, risks, and information market imperfections accompanying such a technology are not well known, we explicitly study the individual roles and combination of learning from friends and relatives (social learning) and extension agents in speeding the adoption of PICS bags.

It is widely recognized that farmers are informed about the presence and efficient use of any novel agricultural technology through social interface with other farmers and extension workers (Genius et al., 2013). The positive role of social learning in the adoption and diffusion of new agricultural technologies is well documented in the literature. For instance, learning from neighbors increased the farmers' adoption of improved seeds and fertilizer in Ethiopia (Krishnan and Patnam, 2013). Likewise, Genius et al. (2013) found that social learning strongly determines irrigation technology adoption and diffusion. Learning through extension services also enables both the adoption and adaptation of technology to local conditions by deciphering information from new research to farmers and helps to explain to research workers the difficulties and constraints farmers face (Anderson and Feder, 2007).

Against this milieu, this paper examines the impact of social learning and extension services on the speed of adoption of PICS bags in Tanzania. We use the time-to-event data for the outcome variable and apply the MIPWRA model in a survival treatment effects framework to achieve this objective. To our knowledge, only a few studies has used the MIPWRA model to analyze the speed of agricultural technology adoption in a multivalued setting. This study builds upon Manda et al. (2020), who used the inverse probability weighted regression (IPWRA) model, but not in a multivalued setting, to estimate the impact of cooperative membership on improved maize variety adoption in Zambia. Other studies (e.g., Beyene and Kassie, 2015; Dadi et al., 2004a; Nazli and Smale, 2016) have used models based on the difficult-to-interpret hazard rates to model the diffusion of agricultural technologies.

The results from MIPWRA give the mean effects, which hide the distributional impact of learning from the two information channels across all categories of adopters (from innovators, early adopters, to laggards). For this reason, we further estimate the heterogeneous effects of social learning and extension services across the entire time to adoption distribution conditional on other covariates using the Laplace regression model. These results contribute to policy-making efficacy because they need policymakers to avoid a 'one-size fits all' approach across the different adopter groups (innovators, early adopters, early majority, late majority and laggards). Most previous studies use the univariate nonparametric Kaplan-Meier estimates to assess a treatment's distributional effects and do not consider the effects of other covariates (e.g., Dadi et al., 2004a; Nazli and Smale, 2016). The other common methods of estimating quantile treatment effects (e.g., Frölich and Melly, 2013) do not consider our outcome variable's censored nature. The Laplace regression model (Bottai and Zhang, 2010) estimates the treatment effects across the percentiles of the time to adoption distribution. Unlike the other methods, this model accounts for the censored outcome variables and does not rely on the proportional hazard assumption like the cox proportional hazard model.

The rest of the article is organized as follows: The next section describes the empirical framework, while Section 3 presents the data and descriptive statistics. Section 4 presents the results and discussion, and the last section draws conclusions and policy recommendations.

2. Empirical Framework

In the agricultural adoption literature, Rogers' Innovation Diffusion Theory (IDT) has been the dominant theory guiding how and why individuals adopt or reject modern technologies. Given that communication is at the core of IDT (Rogers, 2003), we use Rogers' IDT as a guiding framework to explain how communication channels influence the adoption of IPHTs. In our study, there are two distinct classes of communication channels - extension services and social learning.

[1] Channa et al. (2022) define the PICS bag as a three-layer hermetic bag that consists of an outside layer of woven polypropylene and two inner layers of polyethylene.

Extension services represent an organized, formal, and top-down process of communicating information by extension agents to farmers regarding IPHTs. With extension services, farmers are expected to adopt the IPHTs once the extension agents advised them on the technical and financial performance of the innovation.

In contrast, social learning represents an informal process whereby farmers in each social group or neighborhood, or markets communicate with one another and learn about IPHTs. With social learning, farmers are expected to adopt the IPHTs once they are convinced of the performance of the innovation among early adopters.

Communication through extension services occurs between individuals of diverse cultural and socioeconomic backgrounds (extension agent and farmer) while that through social learning occurs between members of similar beliefs, education, socioeconomic status (farmer to farmer). The homophily effect enables fellow farmers to communicate and visit with each other more frequently than extension agents do with farmers. Since they come from the same background and status, they may consider the information exchange about the innovation more credible to change their strong attitudes toward the new innovations. They may then take a risk in investing in the adoption of the innovation. As such, it can be argued that social learning can lead to quicker adoption. On the other hand, the farmers using extension services may take the extension advice of the extension agents (who are considered knowledgeable about innovations) regarding the performance of the innovation more seriously than their fellow farmers' testimony of the performance of the innovation. In this case, it can be argued that extension services can lead to quicker adoption. Considering these two arguments, we can hypothesize that communication channels are systematically associated with the time to adoption of IPHTs. In other words, a farmer may be less or more resistant to adopt PICS bag depending on the communication channel – social learning (a fellow farmer) vis-à-vis extension service (an extension agent)

Depending on their attitudes toward innovation, Rogers (2003) identified five groups of adopters - innovators, early adopters, early majority, late majority, and laggards. For example, the late majority adopters, who are skeptical of change, will only adopt an innovation after they confirm that it has been adopted by the majority. Similarly, laggards, who are traditionally conservative, only adopt an innovation after much resistance or even end up not adopting the innovation. This suggests the need to consider the heterogeneity among households and all parts of the time to adopt the distribution of PICS bags.

Our choice of Rogers' IDT as a guiding framework is to identify the variables to be included in the time to adoption model. IDT suggests that the success of an innovation is determined by the characteristics of the adopters.

2.1. Impact of social learning and extension services on time to the adoption of PICS bags

Agricultural technology choice is a dynamic process that involves a series of judgments based on previous selections and the current or expected economic environment such that simple dichotomous decision models are incapable of capturing the dynamic nature of this process (An and Butler, 2012). Duration models, based on hazard ratios as the effects, have primarily been used to model such as a dynamic process to understand the factors that explain the length of a spell (e.g., Dadi et al., 2004b; Abdulai and Huffman, 2005; Beyene and Kassie, 2015; Canales et al., 2020). In the present study, a spell starts when a farmer becomes aware of the PICS bags for the first time and ends when the farmer adopts the bags. In the subsequent section, we use "time to adoption" or "speed of adoption" to depict the length of the spell.

Popular as they may be, hazard ratios or rates are only suitable for population effects when they are constant, which happens when the treatment enters linearly, and the outcome distribution has a proportional-hazards form (Stensrud et al., 2019). Results based on hazard ratios are also challenging to interpret causality even if the proportional hazard assumption is satisfied (Stensrud et al., 2019). In addition, even though most studies report the average hazard ratio, it may change over time, so its interpretation based on the average may be misleading (Miguel, 2010). To avoid these problems, we use the survival treatment effects, i.e., the likelihood-adjusted censoring (LAC) MIPWRA (hereafter referred to as LAC-MIPWRA), in which the effect of interest is the average treatment effect on the treated (ATT). This measure is easier to interpret because the results are in the same time units as the outcome instead of the relative conditional probabilities in the case of hazard ratios. Second, no linearity in treatment nor proportional-hazards form is required to estimate and interpret the ATT effectively.

In addition to the reasons mentioned above, our specific choice of the MIPWRA model is also based on the following considerations. First, the selection into the social learning and extension services is non-random. That is, households that used social learning and extension services and those that did not may differ systematically. For example, farmers who seek out and receive extension services might be more skilled and motivated than farmers who do not seek such services (Maertens et al., 2021). Therefore, estimating the impact of extension services and social learning without accounting for systematic variation may result in biased estimates. Second, the treatment variable takes on four levels, i.e., no social learning and extension services, social learning only, extension services only, and a combination of social learning and extension services. Propensity score-based approaches are the most popular methods used to deal with the problem of non-random assignment, albeit mainly applied to binary treatment variables. Only recently have more authors started using propensity score-based methods applied to multivalued treatment models (Cattaneo, 2010; Kotu et al., 2017; Manda et al., 2021; Smale et al., 2018).

Before estimating the impacts using survival or hazard-based models, it is a common practice to analyze the distribution of outcome variables, independent of the explanatory factors. To achieve this, we estimate the nonparametric Kaplan–Meier survival estimator (Kaplan and Meier, 1958). The estimator makes no assumptions about the form of the survival function and since the covariates are not modeled, the comparsion of the survival experience is done at the qualitative level across the values of the covariates (Cleves et al., 2008).

To estimate the impact of social learning and extension services using the MIPWRA model, we follow three steps: First, we estimate the parameters of the propensity score model, and then we calculate the inverse probability weights (IPW) for each level of treatment. Specifically, we use the multinomial logit (MNL) model to estimate the propensity score model. The propensity score, in this case, is defined as the probability of using social learning and extension services given observed characteristics (x_i) and can be denoted as:

$$p(x_i) = Pr(T_i = 0\ldots3|x_i) \tag{1}$$

where T_i indicates whether or not a household i had access to social learning and extension services, social learning only, extension services only, and a combination of social learning and extension services, i.e., $T = 0\ldots3$.

We use the maximum likelihood weighted regression (regression adjustment model) in the second step for each treatment level to obtain the household's treatment-specific predicted mean outcomes.[2] The estimated IPW are used to weight the maximum likelihood estimator, and a term in the likelihood function adjusts for right-censored survival times. In the last step, we compute the means of the treatment-specific predicted mean outcomes of the time to adoption. The differences in these outcomes provide the average treatment effects (ATEs):

[2] As with other previous studies, we make the assumption that the outcome model follows a Weibull distribution. We make the same assumption for all the models presented in this study except for the Laplace regression model described in the subsequent sections.

$$ATE_{T_i} = E\left(y_{T_i} - y_0\right) \quad (2)$$

where y_T denotes the potential outcome (time to the adoption of PICs bags) for a household that had used either social learning, extension services, or a combination of the two; and y_0 denotes the outcome for the control category, i.e., no social learning and extension services.

Restricting the computations of the means to the sub-sample of households who have used social learning and extension services, we obtain the average treatment effect on the treated (ATT). The ATT can be defined as:

$$ATT_{\hat{T}_i, \overrightarrow{T}} = E\left\{\left(y_{\hat{T}_i} - y_{0i}\right)|T = \overrightarrow{T}\right\} \quad (3)$$

The ATT requires three different treatment levels: $\hat{t}$ defines the treatment level of the treated potential outcome; 0 is the treatment level of the potential control outcome, and $T = \overrightarrow{T}$ restricts the expectation to include only those individuals who receive treatment level $\overrightarrow{T}$.

Since we use cross-sectional data to estimate the ATE and ATT, identifying the treatment effects relies mainly on three assumptions, i.e., conditional independence (CI), enough overlap, and correct adjustment for censoring. The first two assumptions are common to all methods that use propensity scores, while the third is specific to censored or time-to-event data. The fundamental idea behind the CI assumption is that confounding, if extant, is entirely accounted for by observed covariates (i.e., covariates included *(x)* in Eq. (1)). The overlap assumption ensures that each household could receive any treatment level.[3] The third assumption can be thought of as having two parts. The first part is the expected survival assumption which states that the censoring times are stochastically independent of the potential outcomes, and the treatment-assignment process is conditional on the variables included in the model (Kalbfleisch and Prentice, 2011). The second part is that the technique used to adjust censoring must be correct. This study uses the LAC-MIPWRA to adjust for right-censored times to adoption.[4] To the extent that the MIPWRA uses the LAC to account for censoring, we assume that the outcome model has been correctly specified.

To assess the robustness of the LAC-MIPWRA model results, we also estimate the results using the ordinary least-squares (OLS) regression model and the two most popular methods used in modeling time to event data —the Cox proportional hazards and the survival time regression models.

2.2. Laplace regression model

A linear regression model typically creates a linear relationship between a set of predictor variables and the conditional mean of an outcome variable. However, modeling only the mean may obscure essential aspects of the association between the outcome and its predictors, especially if the outcome distribution is skewed, as with time-to-event data (Beyerlein, 2014). Similarly, as mentioned above, the Cox hazard proportional model is the most popular method of analyzing survival analysis data. However, it is based on the proportional hazard assumption and models the hazard rate instead of the survival time, making it difficult to interpret (Wang and Wang, 2009).

Quantile regression methods capture heterogeneity across the sample in variance and the structural model and relax the proportionality constraint on the hazard (Portnoy, 2003; Wang and Wang, 2009). Considering that the time to adoption is censored, we use the Laplace regression model (Bottai and Zhang, 2010) to model the censoring. Following Bottai and Zhang (2010) and Bottai and Orsini (2013), let D_i be the time to adoption defined above and x_i vector of observed covariates defined in Eq. (1). D_i is censored, and we observe $y_i = \min(D_i, C_i)$, where C_i is a censoring variable. It is assumed that C_i is independent of D_i, conditional on the covariates.

$$D_i = x_i'\beta(p) + \mu_i \quad (5)$$

where $p \in (0, 1)$ is a fixed and given probability and μ_i is an independent and identically distributed residual whose p -quantile equals zero, i.e., $P(\mu_i \leq 0|x_i) = p$ and follows a standard Laplace distribution. It is important to note that Eq. (5) is the same as assuming that $x_i'\beta(p)$ is the p-quantile of the conditional distribution of D_i given x_i, which can be expressed as $P(D_i \leq x_i'\beta(p)|x_i) = p$.

The vast literature informed the variables we included in the equations outlined above on the adoption and diffusion of agricultural technologies. Previous studies have shown that household characteristics such as sex, marital status, education, and household size are important determinants of the rate and speed of adoption of new agricultural technologies (e.g., Beyene and Kassie, 2015; Dadi et al., 2004a; Nazli and Smale, 2016). The sex of the household head is one of the factors influencing the adoption of technologies, with a common finding being that women tend to adopt improved technologies at a lower rate than men because they generally face constraints in terms of access to resources and time (Pender and Gebremedhin, 2007). Previous studies (e.g., Yigezu et al., 2018; Abdulai and Huffman, 2005; Khataza et al., 2018) have shown that education plays a vital role in speeding the adoption of improved agricultural technologies as farmers can easily decipher the information relating to the technology and understand among other things its benefits. Household size is usually used to proxy labour endowment, especially in developing countries, such that the larger the family, the more labour is available for agricultural production. The common finding in studies investigating the adoption of agricultural technologies is that household size is associated with an increase in the adoption rate of such technologies (Kassie et al., 2008; Di Falco and Veronesi, 2013).

The size of the farm and livestock ownership are essential indicators of household wealth and are expected to reduce the time to adopt improved technologies (e.g., Manda et al., 2020; Abdulai and Huffman, 2005). The adoption of agricultural technologies is usually associated with increased costs. Since most of the farmers in developing countries are credit constrained, this limits the adoption of most agricultural technologies. Relaxing such constraints have been shown to increase adoption (Adegbola and Gardebroek, 2007). In the same vein, having a mobile money (M-pesa) and savings account may also indicate access to financial services and resources essential for the adoption of new technologies (Gitonga et al., 2013). The years that a household has lived in a village are usually used as a proxy for social capital and networks, and it has been shown to increase the adoption of new technologies (e.g., Beyene and Kassie, 2015; Kassie et al., 2013).

Access to input and output markets is associated with transaction costs as they can increase time and costs associated with transportation and can adversely affect the adoption of technologies (Teklewold et al., 2013). In this study, we proxy transaction costs with the distance to the village, PICS bags, and district markets.

3. Data and descriptive statistics

3.1. Data

The data comes from a survey conducted using a multistage stratified sampling procedure. The survey was conducted in August and September 2020 in four purposively selected districts—Babati, Kilolo,

[3] In the ensuing sections, we test the overlap assumption using density distributions to assess whether balancing was achieved using the MIPWRA model

[4] We had some situations where we had left-censored observations i.e., cases where farmers adopted the same year they heard about that technology. Following Canales et al. (2020) we added 0.5 to these observations considering that farmers' time to adoption was not necessarily zero.

Kongwa, and Mbozi for two reasons: predominantly maize and beans growing, and the Africa Research in Sustainable Intensification (RISING) East and Southern Africa project has promoted significant postharvest interventions.[5] Next, using probability proportional to size sampling (PPS), ten wards were selected from which 14 villages were chosen randomly. A sampling frame was developed based on the household list with the help of the extension agents from the selected villages. Well-trained enumerators interviewed 579 randomly selected households using CAPI-based survey software called *surveybe*. All participants received a clear explanation of the survey objectives, after which only those who gave verbal consent to participate in the study were interviewed. In this study, we use a sub-sample of 429 households for which we collected data on postharvest technologies.

Detailed information was collected on demographic and socioeconomic characteristics, e.g., household head's age, sex, and education; livestock ownership, farm size, crop production awareness, and adoption of PICS bags.

3.2. Descriptive statistics

Table 1 shows the descriptive statistics of the treatment variables defined Section 2. On average, 13 % of the households did not access information on IPHTs from friends/relatives or extension agents (Table 1). Results further indicate that more farmers obtained information on IPHTs from extension agents (27 %) than from social networks (19 %). Overall, 40 % of the households accessed postharvest-related information from social networks and extension agents.

Section 2 defined the time to adoption as the difference between the year farmers became aware of PICS bags (Fig. 1 a) and the year of the first adoption (Fig. 1 b). In the technology adoption–diffusion process, individuals pass through different phases; awareness, persuasion, decision (adoption or rejection), implementation, and confirmation (Rogers, 1995). Information is sought at all these stages to reduce risk and uncertainty about the usefulness of the technology. Fig. 1a and Table A1 in the appendix show that few farmers were aware of PICS bags between 2000 and 2013. However, we see a significant increase in technology awareness between 2014 and 2020. For instance, 25 % and 38 % of the farmers became aware of PICS bags in 2017 and 2018, respectively. Coincidentally, most of the farmers first adopted PICS bags during this period. This may reflect the awareness campaigns undertaken by several non-governmental organizations (NGOs) to increase the use of airtight containers to reduce postharvest grain losses.

We present the description of variables and summary statistics of the variables considered in the study disaggregated by the treatment variables in Table 2. On average, the time to adopt PICS bags is 2.2 years for farmers who did not learn from friends/relatives or extension agents and 1.5 years for households with access to both. Overall, the time to adoption is 1.7, which is relatively small compared to crop varieties (e.g., Nazli and Smale, 2016; Manda et al., 2020) and conservation agriculture (CA) technologies (Khataza et al., 2018) partly because PICS bags maybe not be as knowledge intensive as CA.[6]

Table 1
Social learning and extension services.

Category	Abbreviation	Frequency (N)	Percent
No social learning and extension	S_0 E_0	55	13.23
Social learning only	S_1 E_0	84	19.49
Extension services only	S_0 E_1	117	27.15
Social learning and extension services	S_1 E_1	173	40.14
Total		429	

On average, about 84 % of the sampled household heads are male. Most of the sample households (83 %) are married and living with their spouses. Households own about 1.9 ha of land, with farmers jointly learning from social networks and extension owning the most significant land. The percentage of households with access to credit is 16 %, while those with mobile money (M-pesa) and savings accounts were 88 % and 23 %, respectively. It is apparent from the results in Table 2 that households who had an opportunity to learn more about PICS bags through social networks and extension agents were more aware of aflatoxins than those who did not at all or knew from only one of the two information channels. We capture the transaction costs regarding acquiring information about PICS bags using the distance to the PICS bags market, input, and output markets (district and village markets), and distance to the extension agent's office. It takes on average about 217 min to walk to the district market and only 27 min to the village market. The distance to the extension agent's office is a proxy for the cost of obtaining information from the agents such that the further away the office is, the more difficult and costily for the farmers to obtain information regarding PICS bags.

Fig. 2 further presents the distribution of the time to adoption by the treatment variables. Like a strip or box plot, the violin plot shows the median as a short horizontal line with a dot, the interquartile range (first-to-third) as a narrow-shaded box, and the lower-to-upper adjacent value range as a vertical line. There seems to be significant heterogeneity in the time to adoption distribution, with clustering in the upper and lower tails of the distributions. To explore this heterogeneity, in the subsequent sections, we use the censored quantile regression model described in Section 2 to estimate the effects of the treatment variable on different levels of the time to adoption distribution conditional on the household and farm characteristics.

4. Empirical results and discussion

4.1. Nonparametric analysis-Kaplan–Meier curve

We first explore the distribution of the time to the adoption of PICS bags and the relationship with learning through social networks and extension agents. Fig. 3 shows the Kaplan–Meier survival estimates for the adoption spell. Most households adopted PICS bags in the first five years of hearing or becoming aware of the technology. In other words, the probability that a household will adopt, given that they have not adopted, increases gradually, as shown by the decline in the survival rate.

Fig. 4 shows the Kaplan–Meier survival estimates for our treatment variables and time to adoption. The nonparametric Kaplan–Meier curve presented in Fig. 4 does not account for other factors affecting adoption time or social and extension learning. The estimates show that farmers who jointly learned from social networks and extension were more likely to adopt PICS earlier than those from either of the two information channels in isolation. Similarly, farmers were more likely to adopt PICS faster if they had access to either social learning or extension agents than those who did not have access to any of the two. The Log-rank test for the equality of the survival function also affirms this result since we reject the null hypothesis that the distribution of the estimates in Fig. 4 is the same ($\chi^2 = 33.08$; $P = 0.000$). It is apparent that there is a potential relationship between the treatment variables and the time to adoption; however, we did not account for other confounding variables that are likely to affect the treatment and outcome variables. We address this issue next using the LAC-MIPWRA and the parametric survival models.

[5] See https://africa-rising.net/east-and-southern-africa/ for details about the project.

[6] The average time to adoption for crop varieties ranged from 6 to 8 years and that CA from 4 to 6 years based on the cited studies.

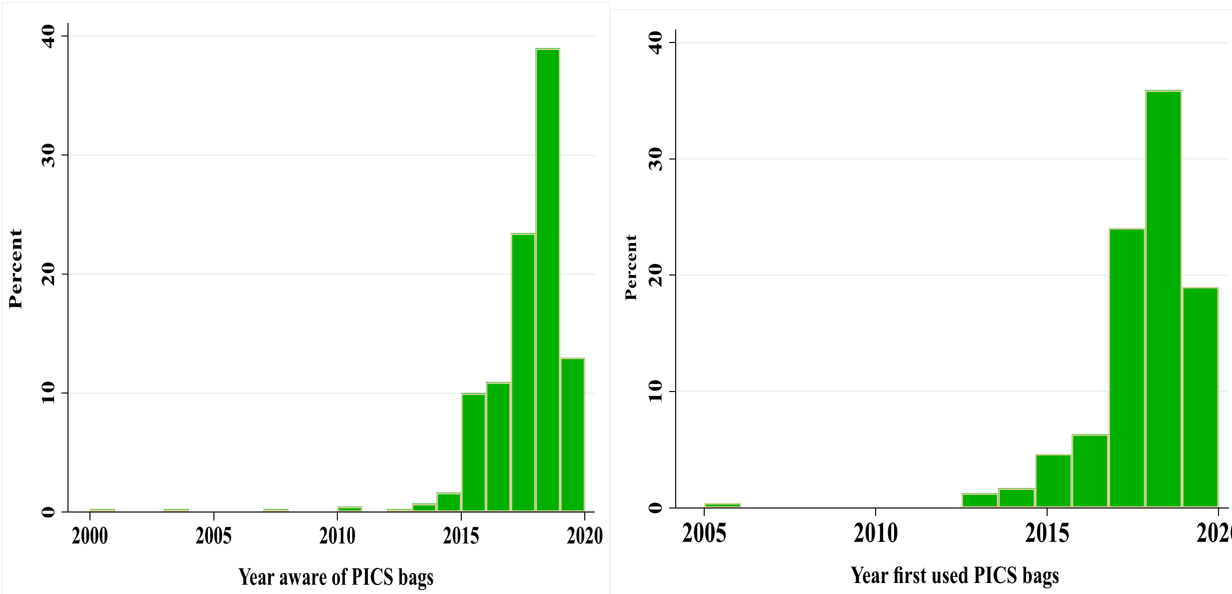

Fig. 1. First year farmer became aware of PICS bags (a) and first year farmer adopted PICS bags (b).

4.2. Multivalued survival treatment effects

4.2.1. Determinants of the time to the adoption of PICS bags

Table 3 presents the second stage parameter estimates from the LAC-MIPWRA model described in Section 3. The first stage results from estimating the multinomial logit model (Eq. (1)) are shown in Table A2 in the appendix. As mentioned in Section 3, the LAC-MIPWRA model results are valid if drawn from observationally similar groups according to the reweighted propensity scores. Results in Fig. A1 show that our four groups' overlap assumption is satisfied after the propensity score reweighting, suggesting that the specification in Section 3 is valid for deriving the impact estimates.

As the study's main objective is to assess the explanatory and treatment variables' impact on the time to adoption, we do not interpret the first-stage results. We report and discuss the results separately for no extension or social learning, social learning, extension and social learning.

4.2.1.1. No extension or social learning. Results in Table 3 indicate that married household heads who did not have access to information on PICS bags from social networks and extension agents were more likely to adopt PICS bags earlier than those who were not married. The time to adoption also decreases with the size of the household, suggesting the importance of labor in adopting IPHTs. The household size is usually a proxy for family labor endowments, especially in developing countries. As expected, farmers who are aware of aflatoxins adopted PICS earlier by 0.5 years. PICS bags create an airtight seal that lowers insect storage loss and counteracts aflatoxin contamination in stored grain (Channa et al., 2019). Therefore, it is envisaged that farmers aware of aflatoxins are more likely to adopt PICS bags. Results also indicate that households with friends or relatives in leadership positions adopt PICS bags faster than those without leadership positions. This variable is a proxy for political connections that impact networking and play a vital role in farmers adopting improved agricultural technologies by facilitating better access to inputs and credit supplied by public institutions (Kassie et al., 2013).

4.2.1.2. Social learning. Consistent with other studies (e.g., Abdulai and Huffman, 2005; Euler et al., 2016; Nazli and Smale, 2016), education reduces the time to adopt for households who obtained information on PICS bags from social networks, pointing to the complementarity of the two. Livestock ownership generally reduces the time to adoption and this result align with those of Manda et al. (2020) and Dadi et al. (2004b) regarding the importance of livestock in technology adoption. Consistent with similar studies (e.g., Gitonga et al., 2013), having a bank account, a proxy for access to financial services and credit, increases the rate of adoption. Contrary to our expectations, the speed of adoption was lower for households who were aware of aflatoxins.

Overall, the variables capturing the transaction costs, i.e., distance to the village, and PICS bags markets, correlate with the adoption speed. The positive coefficients for distances to the market (i.e., district, village, and PICS markets) imply that farmers far away from the market are less likely to adopt PICS bags. The result is expected because of the costs associated with traveling to distant markets, which might prevent farmers from accessing information about airtight storage technologies such as PICS bags. These results are broadly consistent with Tesfaye and Tirivayi (2018). Finally, considering the geographical heterogeneity, the results show that the time to adoption is shorter for Babati households than those in Mbozi district. Relative to other districts, households in Mbozi took more time to adopt PICS bags (on average, 1.9 years). This reflects the differences in climatic conditions, institutional support services, and other factors that might affect the adoption/dissemination of IPHTs such as PICS bags.

4.2.1.3. Extension services. As mentioned above, the size of the household is an important factor in reducing the time to the adoption of PICS bags and so is livestock ownership. Relative to the single woven bags commonly used by farmers to store their harvest, PICS bags are more expensive (Channa et al., 2019); hence, access to credit becomes vital to ease farmers' liquidity constraints. Like other studies (e.g., Abdulai and Huffman, 2005; Alcon et al., 2011; Dadi et al., 2004b), Table 3 shows that the time to adopt PICS bags is reduced with getting credit. Transaction costs were also important in increasing the time to adoption for the households as evidenced by the positive relationship with the distances to village and district markets.

4.2.1.4. Extension and social learning. Results in Table 3 indicate that being a male household head reduces adoption time for households who jointly learned from social networks and extension. Unlike households who had no access to either social learning or extension, the speed of adoption increased for households heads who were married and had access to the two communication channels. As expected, land ownership

Table 2
Descriptive statistics.

Variable	Variable description	S_0 E_0		S_1 E_0		S_0 E_1		S_1 E_1		All	
		Mean (*N* = 57)	SD	Mean (*N* = 84)	SD	Mean (*N* = 117)	SD	Mean (*N* = 173)	SD	Mean (*N* = 429)	SD
Dependent variable											
Time to adoption	Time to the adoption of PICS bags (years)	2.228	1.443	2.06	1.616	1.594	1.352	1.457	1.483	1.713	1.496
Independent variables											
Sex	Sex of the household head (1 = Male)	0.842	0.368	0.869	0.339	0.786	0.412	0.867	0.341	0.842	0.365
Marital status	Married and living with spouse (1 = Yes, 0 = otherwise)	0.825	0.384	0.798	0.404	0.803	0.399	0.85	0.358	0.824	0.382
Household size	Household size in adult equivalent (number)	4.694	2.41	4.797	2.076	4.282	1.934	4.937	2.212	4.7	2.151
Education	Education level of household head (years of formal)	6.877	3.295	6.524	2.98	6.733	4.609	7	2.222	6.818	3.295
Livestock	ownership of livestock in Tropical Livestock Units (TLU)	2.017	2.502	2.57	5.095	2.18	2.988	5.027	3.039	3.377	19.481
Land	Total land owned in hectares	1.975	1.905	1.735	1.448	1.781	2.188	2.059	2.246	1.909	2.051
Years in village	Number of years household head has lived in the village	33.842	18.642	33.94	15.399	33.513	16.502	33.306	17.46	33.557	16.927
Credit	Access to credit (1 = Yes, 0 = otherwise)	0.088	0.285	0.19	0.395	0.077	0.268	0.231	0.423	0.162	0.369
M-Pesa account	Household has mobile money account (1 = Yes, 0 = otherwise)	0.807	0.398	0.869	0.339	0.846	0.362	0.925	0.264	0.877	0.329
Savings account	Household has savings account (1 = Yes, 0 = otherwise)	0.211	0.411	0.143	0.352	0.299	0.46	0.231	0.423	0.23	0.421
Aware of aflatoxin	Household aware of aflatoxin (1 = Yes, 0 = otherwise)	0.07	0.258	0.298	0.46	0.12	0.326	0.393	0.49	0.258	0.438
Leadership	Household has friends/ relatives in leadership positions (1 = Yes, 0 = otherwise)	0.368	0.487	0.464	0.502	0.393	0.491	0.491	0.501	0.443	0.497
PICS bag market	Distance to PICS bag market in walking minutes	150.491	115.37	120.179	133.846	131.983	125.09	134.451	125.033	133.121	125.457
District market	Distance to district market in walking minutes	216.842	135.21	187.56	137.791	185.239	106.51	209.075	289.845	199.439	207.05
Village market	Distance to village market in walking minutes	27.193	26.297	26.012	30.023	28.274	38.103	34.532	40.175	30.202	36.256
Extension office	Distance to extension office in walking minutes	45.281	60.207	45.845	49.712	37.513	35.19	42.081	53.032	41.998	49.172
Number of observations		57		84		117		173		431	

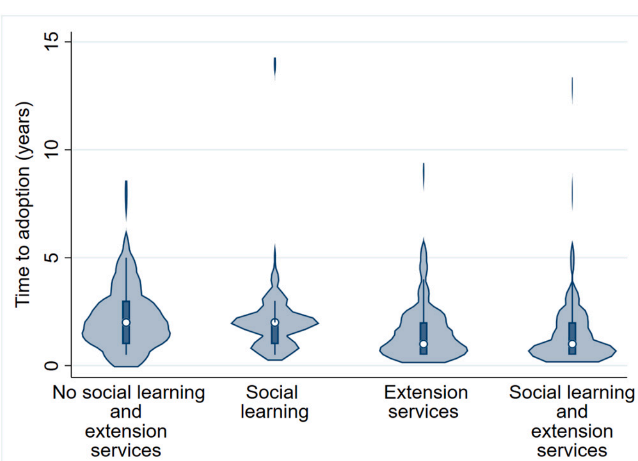

Fig. 2. Violin plots for the distribution of the time to adoption by no social learning and extension services, social learning, extension services, and social learning and extension services.

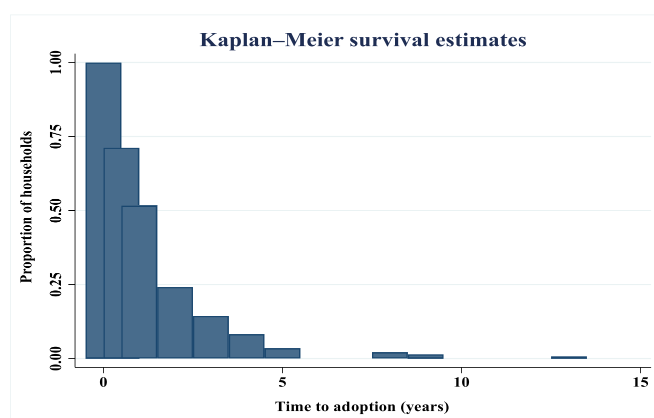

Fig. 3. The time to adoption of PICS bags.

minimizes the time to adoption, consistent with most of the studies on agricultural technology adoption (e.g., Euler et al., 2016). Similar to the households that accessed only extension services, credit was an

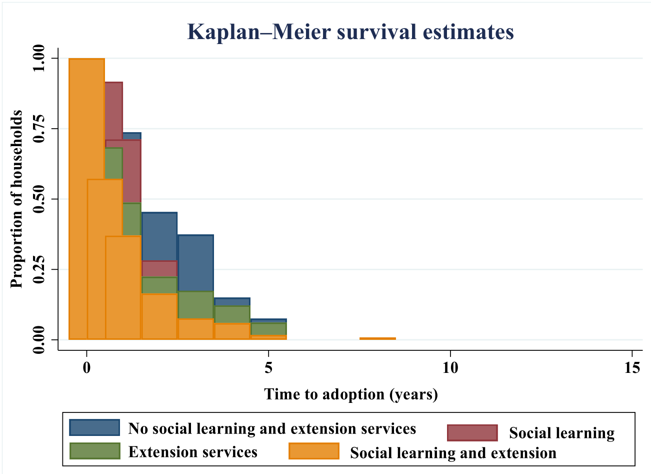

Fig. 4. The time to adoption of PICS by no social learning and extension services, social learning, extension services and social learning and extension services.

Table 3
Determinants of the time to adoption of PICS bags.

Variable	Time to adoption (years)			
	(S_0 E_0)	(S_1 E_0)	(S_0 E_1)	(S_1 E_1)
Sex	1.131	−0.060	0.088	−0.448**
	(0.745)	(0.158)	(0.421)	(0.223)
Marital status	−0.884**	−0.107	−0.364	0.560**
	(0.426)	(0.214)	(0.288)	(0.261)
Household size	−0.250***	0.058	−0.071*	0.016
	(0.073)	(0.050)	(0.042)	(0.027)
Education	−0.012	−0.044**	0.022	−0.030
	(0.048)	(0.020)	(0.021)	(0.031)
Livestock	−0.035	−0.010**	−0.090**	0.002*
	(0.061)	(0.004)	(0.036)	(0.001)
Land	0.033	0.006	−0.025	−0.077***
	(0.085)	(0.045)	(0.023)	(0.028)
Years in village	−0.005	0.001	−0.002	0.005
	(0.005)	(0.002)	(0.008)	(0.006)
Credit	−0.413	−0.286	−0.789***	−0.634***
	(0.709)	(0.178)	(0.146)	(0.079)
M-Pesa account	−0.328	0.045	−0.190	0.010
	(0.287)	(0.192)	(0.223)	(0.279)
Savings account	−0.258	−0.224***	−0.179	0.101
	(0.396)	(0.085)	(0.316)	(0.216)
Aware of aflatoxin	−0.511***	0.581***	−0.026	−0.170
	(0.174)	(0.104)	(0.181)	(0.156)
Leaders	−0.991***	0.004	0.158	0.223
	(0.228)	(0.177)	(0.267)	(0.155)
Ln District market	−0.131	−0.167*	0.228**	0.015
	(0.412)	(0.102)	(0.103)	(0.060)
Ln Village market	−0.402	0.167*	0.155*	−0.075
	(0.329)	(0.102)	(0.084)	(0.059)
Ln PICS bag market	0.182	0.083*	−0.113	0.211***
	(0.204)	(0.048)	(0.102)	(0.045)
Babati district	0.981	−0.411**	0.061	−0.324
	(1.309)	(0.204)	(0.281)	(0.345)
Kilolo district	−0.709	0.067	0.358	−0.287
	(1.336)	(0.131)	(0.317)	(0.194)
Kongwa district	0.783	0.067	0.584	−1.018***
	(0.717)	(0.080)	(0.363)	(0.227)
Constant	4.319	0.864	0.392	0.043
	(3.081)	(0.751)	(1.184)	(0.395)
Observations	429	429	429	429

Note: Cluster robust standard errors at the ward level are reported in parenthesis.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

important determinant of the time to adoption for households who had access to extension and social learning. Results further show that increase in the distance to the PICS bag markets reduces the speed of adoption as explained above. Lastly households in Kongwa district adopted PICS bags earlier than those in Mbozi district.

4.2.2. *Impact of social learning and extension services*

Table 4 shows the effect on the subpopulations of households who learned from social networks and extension agents in isolation and jointly, i.e., the ATT.[7] The ATE results are presented in Table A3 in the appendix. The ATT results indicate that the average adoption time would be 4.3 years if no household accessed social learning and extension services. However, if the households learned only from social networks, the average time to adoption would decrease by 2.2 years, a 51 % reduction compared with the potential outcome of no social and extension learning. These results are broadly consistent with those of Genius et al. (2013) and Khataza et al. (2018).

Similarly, if households only learned from extension agents, the average time to adoption would decrease by 2.1 years, an estimated 49 % reduction relative to the case of no social and extension learning. The ATT estimates also indicate that the collective knowledge from social networks and extension agents is associated with the most significant decline in the years to adoption. On average, joint learning from social networks and extension agents would reduce the average time to adoption by 2.6 years, a 61 % reduction in the years to adoption relative to the potential outcome of no social learning and extension services. These results are consistent with Genius et al. (2013), who contend that the presence of the other enhances the effectiveness of each type of information channel. Further, they explain that extension services will be more effective than social networks for speeding up the adoption process in areas with a critical mass of adopters.

4.3. *OLS, Cox Proportional hazard, and survival time models*

We also estimated the results using OLS, Cox Proportional Hazard, and survival time models to provide a robustness check for the LAC-MIPWRA results (Table 5). For brevity, we concentrate on the results from the treatment variables only. The OLS estimates show that the time to adoption reduces by 0.68 and 0.72 years with extension learning only and joint learning from social networks, respectively.

Table 5 presents the coefficient and hazard ratio estimates. We use the hazard ratio to interpret our results since the Cox Proportional Hazard and survival time models are based on the hazard ratio. A hazard ratio greater (less) than one indicates that the variable reduces

Table 4
Impact of social and extension learning on time to adoption of PICS bags.

Treatment	Potential outcome mean (without social learning and extension services)	ATT	Percent reduction (%)
S_0 E_0	4.325***		
	(0.541)		
S_1 E_0		−2.188***	51
		(0.575)	
S_0 E_1		−2.126***	49
		(0.473)	
S_1 E_1		−2.626***	61
		(0.685)	

Note: Cluster robust standard errors at the ward level are reported in parenthesis.
*** $p < 0.01$.

[7] In survival analysis language, this is also known as the effect in a well-defined subpopulation that is at-risk.

Table 5
Estimation results for OLS, Cox Proportional Hazard, and survival time models.

Variable	OLS	COX PH		Survival time	
	Coefficient	Coefficient	Hazard ratio	Coefficient	Hazard ratio
S_1 E_0	−0.119	0.213**	1.238	0.188	1.207
	(0.150)	(0.095)	(0.169)	(0.134)	(0.231)
S_0 E_1	−0.680**	0.445***	1.560***	0.629***	1.876***
	(0.274)	(0.167)	(0.220)	(0.239)	(0.351)
S_1 E_1	−0.729*	0.588***	1.801***	0.708**	2.029***
	(0.364)	(0.188)	(0.250)	(0.300)	(0.394)
Sex	0.246**	−0.252**	0.777	−0.323**	0.724
	(0.099)	(0.102)	(0.141)	(0.135)	(0.177)
Marital	−0.149	0.186	1.204	0.233	1.262
status	(0.167)	(0.155)	(0.225)	(0.183)	(0.316)
Household	−0.028	0.014	1.014	0.027	1.028
size	(0.030)	(0.022)	(0.023)	(0.033)	(0.032)
Education	−0.009	0.002	1.002	0.001	1.001
	(0.013)	(0.007)	(0.014)	(0.012)	(0.019)
Livestock	0.003***	−0.002***	0.998***	−0.002***	0.998***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Land	−0.048	0.048***	1.049**	0.063***	1.065**
	(0.029)	(0.018)	(0.021)	(0.022)	(0.027)
Years in	0.004	−0.002	0.998	−0.006	0.994
village	(0.004)	(0.002)	(0.003)	(0.004)	(0.004)
Credit	−0.626***	0.497***	1.644***	0.792***	2.207***
	(0.123)	(0.061)	(0.166)	(0.087)	(0.296)
M-Pesa	0.058	0.170*	1.185	0.113	1.120
account	(0.094)	(0.098)	(0.167)	(0.108)	(0.202)
Savings	−0.152	0.221**	1.248**	0.192	1.212
account	(0.197)	(0.090)	(0.134)	(0.187)	(0.211)
Aware of	0.168	0.033	1.033	0.008	1.008
aflatoxin	(0.212)	(0.111)	(0.113)	(0.165)	(0.167)
Leadership	0.101	0.017	1.017	−0.028	0.973
	(0.093)	(0.067)	(0.089)	(0.079)	(0.123)
Ln District	0.054	−0.040	0.961	−0.053	0.949
market	(0.060)	(0.038)	(0.058)	(0.060)	(0.083)
Ln Village	0.091	−0.038	0.962	−0.023	0.977
market	(0.133)	(0.061)	(0.046)	(0.091)	(0.071)
Ln PICS bag	0.056	−0.037	0.963	−0.073	0.929
market	(0.063)	(0.038)	(0.034)	(0.058)	(0.046)
Ln Extension	−0.061	0.039	1.039	0.042	1.042
office	(0.065)	(0.033)	(0.052)	(0.059)	(0.071)
Babati	−0.434***	0.183**	1.200	0.402***	1.495**
district	(0.092)	(0.072)	(0.163)	(0.105)	(0.298)
Kilolo district	−0.363**	0.008	1.008	0.166	1.181
	(0.157)	(0.135)	(0.108)	(0.189)	(0.183)
Kongwa	−0.394**	−0.180**	0.835	0.105	1.111
district	(0.130)	(0.080)	(0.129)	(0.110)	(0.234)
Constant	1.908**		1.238	−1.289	1.207
	(0.601)		(0.169)	(0.843)	(0.231)
Observations	429		429	429	429

Note: Cluster robust standard errors at the ward level are reported in parenthesis.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

(increases) the time to adoption. Results from the two models suggest that the time to adoption by households who learned from social networks and extension agents was more likely to reduce by 80 % and 103 %, respectively, compared to those who did not know about PICS bags from this information channels. This speed of adoption is much higher than that if the household were to learn from only the extension agents (56 % and 88 %). The impacts of the treatment variables and the other explanatory variables are similar to the LAC-MIPWRA results regarding the direction of the effects with minimal differences in the magnitudes.

We also estimated parsimonious models of the models, i.e., without other explanatory variables presented in Table 5 to assess how sensitive our results are to other factors. Results presented in Table A4 are relatively similar to those in Table 5, which implies that selection bias may not be a very big problem in study.

4.4. Laplace regression quantile survival effects

The violin plots presented in Fig. 2 suggest that the effects of learning from social networks and extension agents on time to adoption are likely to be heterogeneous. Unlike the Kaplan–Meier curves (Fig. 3 and Fig. 4), which give estimates at the univariate level, Table 6 reports the estimated quantile effects of social and extension learning on the 10th–90th quantiles or percentiles of the outcome variable conditional on the characteristics of the households. The first (10th) quantile includes households with the fastest speed of adoption, while the opposite is true for the farmers in the 90th quantile. The results have the expected signs and show that social and extension learning impacts are not homogenous but vary significantly across the distribution of the adoption spell. We also reject the null hypothesis that the treatment effects are equal across the time to adoption percentiles. The results displayed in Table 6 are consistent with those in Tables 3 and 4 as they indicate that the combination of social and extension learning results in the most significant reduction in the time to adoption than if farmers learned from social networks or extension agents in isolation, regardless of the quantile in consideration.

Moreover, the results show that the impact of social learning and extension services is more pronounced in the upper sections than in the lower area of the distribution. For instance, learning from social networks reduces the time to adoption by 0.6 years in the 80th quantile compared with those in the 60th quantile (0.45 years). Similarly, learning jointly from social networks and extension agents reduces the speed of adoption by 0.37 and 1.23 years in the 10th and 90th quantiles, respectively.

5. Summary and concluding remarks

Most cereals, pulses, and oilseeds, such as maize, beans, and groundnuts, which form the foundation for food, income, and nutrition for most households in Tanzania, are highly susceptible to postharvest losses due to insect damage and aflatoxin contamination. Previous studies show that adopting improved postharvest technologies such as PICS bags can reduce these problems. However, in most of these studies, much attention has been given to evaluating the effectiveness of the PICS bags based on on-farm trials and does not consider the speed of adoption. Furthermore, there is a dearth of evidence on the role of social networks and access to extension access on the time it takes for farmers

Table 6
Estimation results for the Laplace regression model.

Quantile	S_1 E_0	S_0 E_1	S_1 E_1
Q10	0.090	−0.366***	−0.365***
	(0.141)	(0.140)	(0.125)
Q20	−0.016	−0.513**	−0.515**
	(0.210)	(0.215)	(0.208)
Q30	−0.094	−0.860***	−1.025***
	(0.268)	(0.206)	(0.211)
Q40	−0.114	−0.990***	−1.130***
	-(0.182)	(0.214)	(0.21)
Q50	−0.205	−0.708***	−1.061***
	-(0.189)	(0.243)	(0.247)
Q60	−0.458*	−0.716***	−0.881***
	(0.248)	(0.270)	(0.269)
Q70	−0.486	−1.021***	−1.110***
	(0.343)	(0.358)	(0.346)
Q80	−0.602*	−1.032***	−1.218***
	(0.357)	(0.391)	(0.346)
Q90	−0.446	−0.915*	−1.229***
	(0.411)	(0.517)	(0.443)
Test for differences in the effects	$\chi2(27)$ =125.81***		

Note: Bootstrapped standard errors in parentheses.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

to adopt PICS bags in Tanzania. This paper contributes to the empirical literature by examining the interdependent impacts of learning from friends/relatives and extension agents on the speed of PICS bags adoption in Tanzania. We apply the doubly robust multivalued inverse probability weighted regression (MIPWRA) model in a survival treatment effects framework to estimate the impact and the Laplace regression model to evaluate the heterogeneous effects of the two information transmission channels.

Overall, results indicate that learning from friends/relatives and extension agents reduces the time it takes for farmers to adopt PICS bags. On average, social and extension learning reduces the time to adoption by 51 % and 49 %, respectively. The results further show that the rate at which farmers adopted the technology was faster when they jointly learned from the two information channels (61 %) than from the individual sources. This indicates that these channels are complements rather than substitutes. Furthermore, results from the Laplace regression model suggest that the effects are not homogenous but heterogeneous, as the marginal impacts of information transmission are more prominent for households in the upper quantiles and smaller for those in the lower quantiles of the time adoption distribution.

Overall, two policy issues emerge from our research. First, recognizing the complementarity of learning from friends/relatives and extension agents in designing public extension policies is vital to increasing the rate at which farmers adopt improved agricultural technologies. Although agricultural extension is also provided by private institutions, in most cases, this is usually offered by public institutions that face several challenges, including but not limited to inadequate extension staff and transaction costs associated with covering extensive distances to train farmers. Social learning could complement public extension as farmers can quickly learn from other farmers even if few have access to extension; hence events promoting community interactions, such as field days and demonstrations, are essential.

Second, the significance of access to credit in reducing the time to adoption suggests that the provision of loans or subsidies to farmers can be one of the policy objectives that can be pursued for farmers to adopt PICS bags. With PICS bags being relatively new, there may be some uncertainties about their effectiveness; hence the provision of a one-time use subsidy to build awareness and reduce risk can help generate demand for such a novel technology (Omotilewa et al., 2019).

Though we have tried to rigorously isolate the impact of social and extension learning, a significant limitation of our study is the definition of social learning. Future studies should explore using alternative definitions and construction methods of social learning, such as using geographical positioning systems (GPS) to measure the distances between friends or neighbors who had access to or adopted PICS bags and those who did not. Further, the data we used is cross-sectional and the methodology does not consider unobserved heterogeneity. Even though we conditioned our estimation on a rich set of observed covariates, the conditional independence assumption on which our model is based is strong and cannot be tested. Therefore, without controlling for the unobserved characteristics, biased estimates may be obtained. Future studies should consider using panel data or frailty models to effectively control for these characteristics.

CRediT authorship contribution statement

Julius Manda: Conceptualization, Data curation, Formal analysis, Methodology, Software, Writing – original draft. **Shiferaw Feleke:** Writing – review & editing. **Christopher Mutungi:** Data curation, Writing – review & editing. **Adane H. Tufa:** Writing – review & editing. **Bekunda Mateete:** Writing – review & editing. **Tahirou Abdoulaye:** Writing – review & editing. **Arega D. Alene:** Writing – review & editing.

Data availability

Data will be made available on request.

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Appendix A

Table A1
Year of awareness and first adoption of PICS bags (% of farmers).

Year	Awareness	First adoption
2000	0.23	
2003	0.23	
2005		0.45
2007	0.23	
2010	0.46	
2012	0.23	
2013	0.7	1.36
2014	1.62	1.81
2015	9.98	4.98
2016	10.9	6.79
2017	23.43	25.79
2018	38.98	38.46
2019	12.3	19.91
2020	0.7	0.45

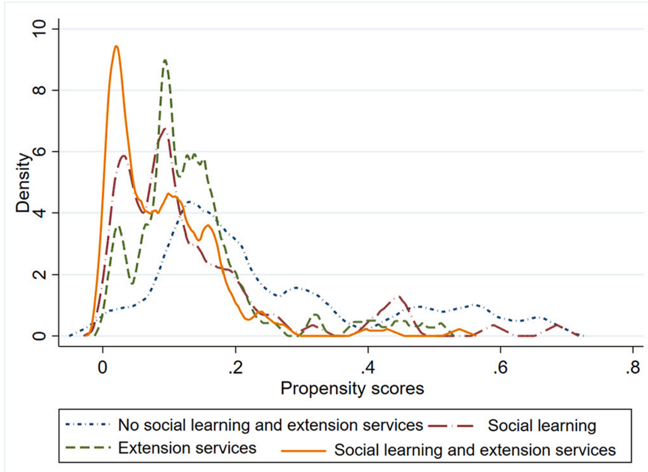

Fig. A1. Balanced plots for the time to adoption by social and extension learning.

Table A2
Determinants of social learning and extension services.

Variable	Social learning	Extension services	Social learning and extension services
Sex	0.665	−0.854*	−0.366
	(0.457)	(0.466)	(0.497)
Marital status	−0.666	0.366	0.169
	(0.528)	(0.400)	(0.600)
Household size	0.082	−0.086	0.071
	(0.095)	(0.128)	(0.133)
Education	−0.058	−0.016	−0.013
	(0.059)	(0.044)	(0.042)
Livestock	0.018	−0.003	0.023
	(0.034)	(0.066)	(0.035)
Land	−0.046	0.002	0.007
	(0.108)	(0.161)	(0.078)
Years in village	−0.002	0.005	0.003
	(0.008)	(0.009)	(0.012)
Credit	0.711*	−0.560	0.855*
	(0.390)	(0.504)	(0.493)
M-Pesa account	0.673	0.509	1.377***
	(0.580)	(0.403)	(0.406)
Savings account	−0.601	0.413	−0.174
	(0.509)	(0.311)	(0.511)
Aware of aflatoxin	2.056***	0.944*	2.489***
	(0.714)	(0.561)	(0.722)
Leaders	0.139	0.325	0.367
	(0.320)	(0.408)	(0.264)
Ln District market	−0.207	−0.181	−0.194
	(0.297)	(0.273)	(0.199)
Ln Village market	−0.124	−0.320**	0.067
	(0.172)	(0.129)	(0.199)
Ln PICS bag market	−0.219**	0.074	0.126
	(0.103)	(0.134)	(0.146)
Ln Extension office	0.241	0.224	−0.038
	(0.345)	(0.300)	(0.250)
Babati district	−0.645	−0.631*	−0.233
	(0.418)	(0.346)	(0.467)
Kilolo district	0.497	0.238	0.899***
	(0.308)	(0.269)	(0.267)
Kongwa district	−0.430**	−2.660***	−2.233***
	−0.645	−0.631*	−0.233
Constant	1.130	1.901	−0.646
	(2.500)	(1.875)	(1.831)
Observations	429	429	429

Note: Cluster robust standard errors at ward level are reported in parenthesis.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Table A3
Impact of social learning and extension services on time to adoption of PICS bags (ATE).

Treatment	Potential outcome (without social learning and extension services)	ATE
S_0 E_0	4.209***	
	(0.991)	
S_1 E_0		−1.930*
		(1.027)
S_0 E_1		−2.101**
		(0.823)
S_1 E_1		−2.564**
		(1.172)

Note: Cluster robust standard errors reported in parenthesis.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Table A4
Estimation Results for OLS, Cox Proportional Hazard and survival time models (parsimonious models).

	OLS	COX PH		Survival time	
	Coefficient	Coefficient	Hazard ratio	Coefficient	Hazard ratio
Social learning	−0.169	0.278**	1.321**	0.297	1.346
	(0.259)	(0.132)	(0.175)	(0.194)	(0.261)
Extension	−0.634***	0.444***	1.558***	0.524***	1.689***
	(0.228)	(0.142)	(0.222)	(0.184)	(0.311)
Social learning and extension	−0.771***	0.693***	1.999***	0.756***	2.129***
	(0.221)	(0.130)	(0.260)	(0.183)	(0.389)
Constant	2.228***			−1.413***	
	(0.190)			(0.153)	
Observations	429	429		429	

Note: Cluster robust standard errors at ward level are reported in parenthesis.
** $p < 0.05$.
*** $p < 0.01$.

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