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

*Julius Manda

*International Institute of Tropical Agriculture (IITA), P.O Box 10, Arusha, Tanzania*

Shiferaw Feleke

*International Institute of Tropical Agriculture (IITA), Dar es Salaam, Tanzania*

Christopher Mutungi

*International Institute of Tropical Agriculture (IITA), Dar es Salaam, Tanzania*

Adane H Tufa,

*International Institute of Tropical Agriculture (IITA), Lilongwe, Malawi*

Bekunda Mateete

*International Institute of Tropical Agriculture (IITA), Arusha, Tanzania*

Arega D Alene

*International Institute of Tropical Agriculture (IITA),Nairobi, Kenya*

Tahirou Abdoulaye

*International Institute of Tropical Agriculture (IITA), Bamako, Mali*

**Acknowledgements**

The authors gratefully acknowledge financial support from United States Agency for International Development (USAID) through the Africa Research in Sustainable Intensification for the Next Generation (Africa RISING) program as part of the US Government's Feed the Future Initiative. We thank Mussa Nya of the International Institute of Tropical Agriculture (IITA) who ably supervised the data collection process.

**Abstract**

This study examines the impacts of social learning and extension services on the time it takes to adopt an improved postharvest technology called Purdue Improved Crop Storage (PICS) bag in Tanzania. We utilized the doubly robust multivalued inverse probability weighted regression (MIPWRA) model in a survival treatment effects framework to estimate the impact. We also applied the Laplace regression model to evaluate the heterogeneous effects of the two information sources. Overall, results from the MIPWRA indicate that social learning and extension services reduce the time to adopt PICS bags by 51% and 49%, respectively. The results further show that the speed at which farmers adopted the technology was faster when using the two information sources jointly (61%) than individually. The results from the Laplace regression model also show that the impacts of social learning and extension services vary significantly across the time to adoption distribution. The marginal impacts of the two information sources are more meaningful for the households in the upper quantiles of the distribution, compared to the lower quantiles representing the early adopters. Designing policies that account for the complementarity of the two sources of information is essential to increasing the adoption of PICS bags in Tanzania.

*Keywords*: Postharvest losses, improved postharvest technologies, social learning, extension services, Tanzania.

## 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). These losses reduce the quantities available for sale and future consumption, coupled with income loss through price discounts for damaged crop produce (Kadjo et al., 2016) for most smallholder farmers. 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. Notwithstanding the significant variations in the estimates, postharvest losses are generally estimated at over 20% for the major cereals and pulses (Abass et al., 2014; Mutungi and Affognon, 2013; Abass et al., 2018). The primary loss agent for stored maize is the infestation by insects infestations, such as the larger grain borer (LGB) and the maize weevils (Vowotor 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 also 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. Adopting improved postharvest storage technologies (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 considerably 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

[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.

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. Despite these positive effects of airtight storage containers, there is limited empirical evidence on the adoption dynamics of improved postharvest technologies in Tanzania. The empirical literature on agricultural technology adoption continues to ignore its dynamics (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 mainly based on ex-ante data and on-station experiments. However, technology adoption is not a one-off static decision but rather a dynamic process that entails information gathering and learning (Jabbar et al. 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 done the assessment at the extensive margin and did not consider the dynamic nature of technology adoption at the intensive margin. As such, rigorous studies on the dynamics 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 in the literature by examining the determinants of the time to adopt the 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 time it takes to adopt 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, no study has used the MIPWRA model to analyze the dynamics 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. Using the MIPWRA, we measure the impact of the learning from social networks and extension services on time to PICS adoption.

The results from MIPWRA give the mean effects, which hide the distributional impact of learning from the two information sources 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. 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., 2004; 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

### 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, Burton and Ozanne, 2004; Abdulai and Huffman, 2005; Beyene and Kassie, 2015; Canales, Bergtold and Williams, 2020). In the present study, a spell starts at the time when a farmer becomes aware of the PICS bags for the first time and ends at the time 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 (StataCorp, 2015). 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 A., 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).

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:

$$p(x_i) = Pr(T_i = 0 \ldots 3|x_i) \quad (1)$$

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…3.

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):

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

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:

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

[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.

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 $T = \vec{T}$ restricts the expectation to include only those individuals who receive treatment level $\vec{T}$.

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 equation 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, 2002). 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 (StataCorp, 2015).

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,

---

[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.

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 equation 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.

$$D_i = \acute{x}_i\beta(p) + \mu_i \tag{5}$$

Where $p \in (0,1)$ is a fixed and given probability and $\mu_i$ 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 equation 5 is the same as assuming that $\acute{x}_i\beta(p)$ is the $p$-quantile of the conditional distribution of $D_i$ given $x_i$, which can be expressed as $P(D_i \leq \acute{x}_i\beta(p)|x_i) = p$.

## 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, Kongwa, and Mbozi for two reasons: predominantly maize and beans growing, and the Africa 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. All the villages in the selected wards were listed, and a random sampling led to 14 villages. 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. On average, 13% of the households did not access information on improved postharvest technologies from friends/relatives or extension agents (Table 1). Results further indicate that more farmers obtained information on postharvest technologies from extension agents (27%) than from social networks (19%). Overall, 40% of the households accessed postharvest-related information from social networks and extension agents.

**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 |

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

| | | | |
|---|---|---|---|
| Social learning and extension services | $S_1 E_1$ | 173 | 40.14 |
| Total | | 429 | |

Section 2 defined the time to adoption as the difference between the year farmers became aware of PICS bags (Figure 1 a) and the year of the first adoption (Figure 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. Figure 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 2014-2020. 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.

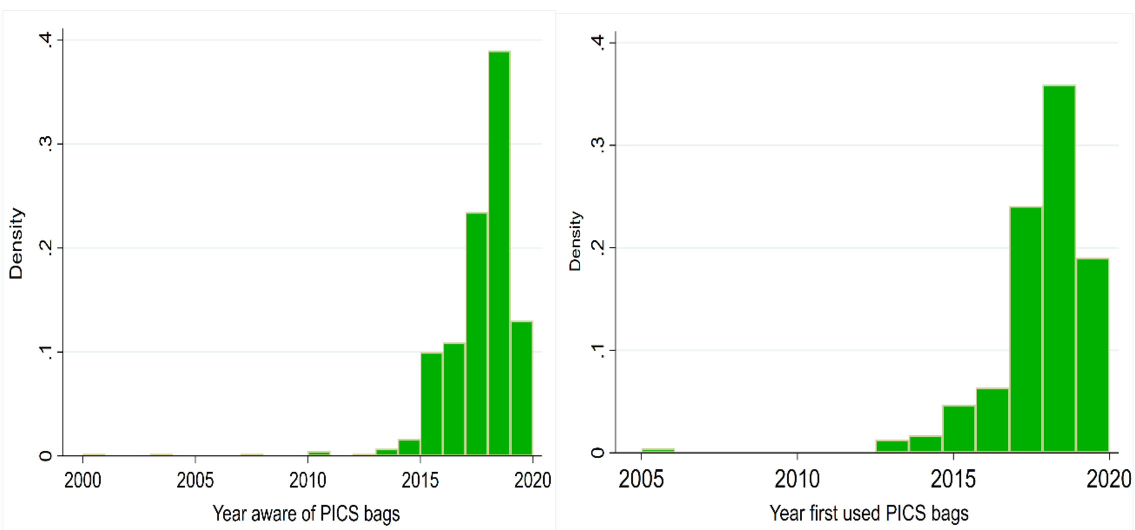


**Figure 1: Awareness (a) and first adoption (b) of PICS bags**

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]. On average, about 84% of the sampled household heads are male. 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 sources of information. 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.

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

1 **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 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 | |

2

Figure 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.

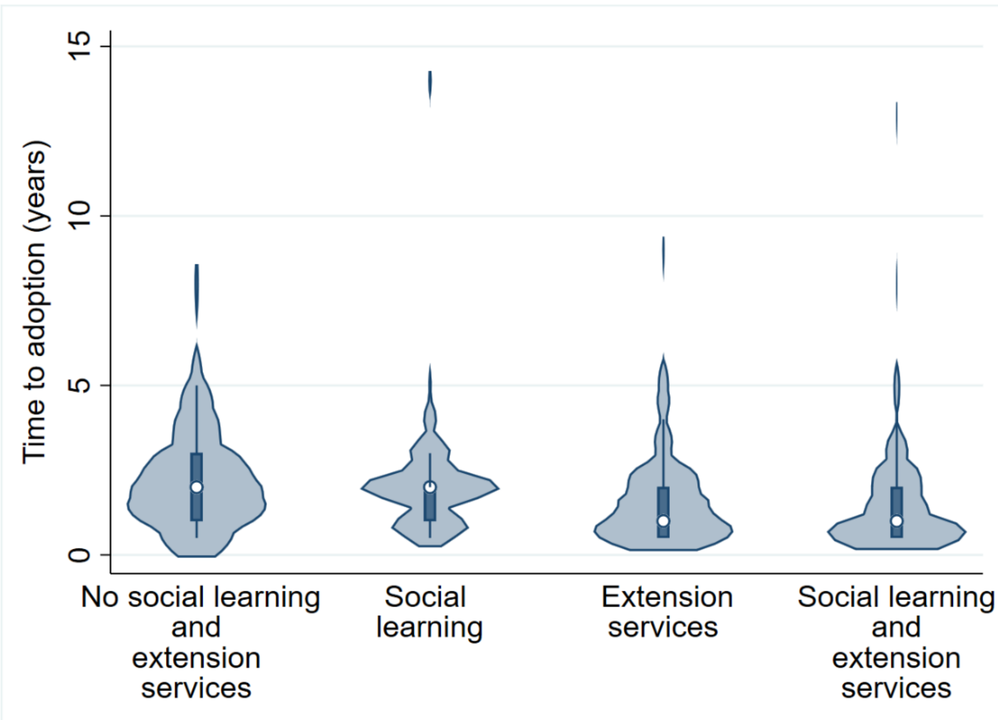


**Figure 2: Violin plots for the distribution of the time to adoption by social learning and extension services**

## 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. Figure 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.

Figure 4 shows the Kaplan–Meier survival estimates for our treatment variables and time to adoption. The nonparametric Kaplan–Meier curve presented in Figure 4 does not account for other factors that may affect 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 didn't have access to any of the two. The Log-rank test for the equality of survival function also affirms this result since we reject the null hypothesis that the distribution of the estimates in Figure 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 didn't account for other confounding variables which are likely to affect the treatment and outcome variables. We address this issue next using the LAC-MIPWRA and the parametric survival models.

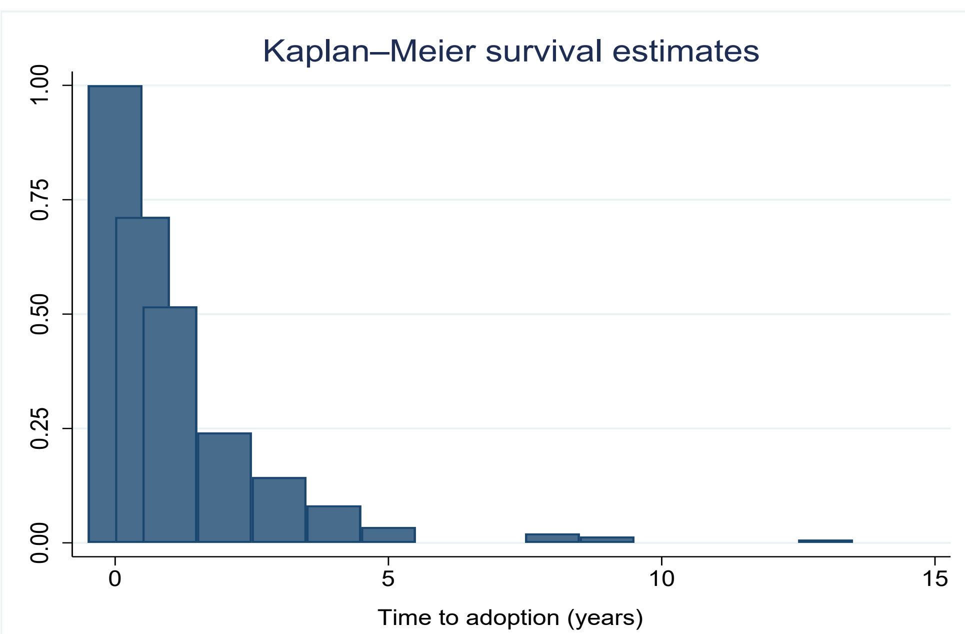


**Figure 3: The time to adoption of PICS**

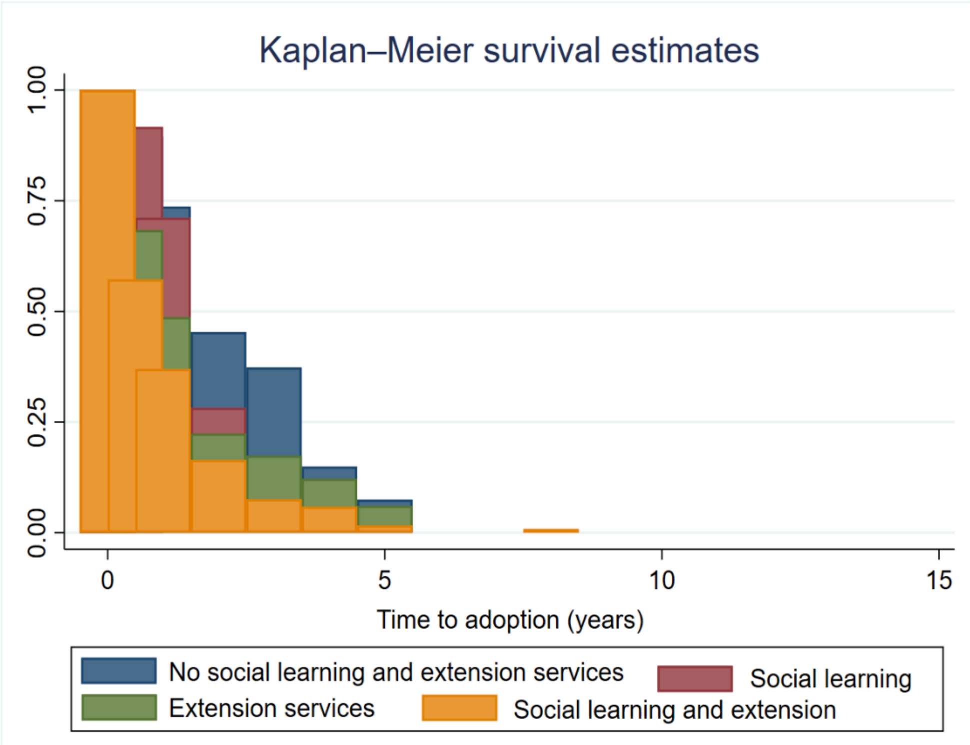


**Figure 4: The time adoption of PICS by the social learning and extension services**

## 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 (equation 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 Figure 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 don't interpret the first stage results. Results in Table 3 indicate that being a male household head reduces adoption time for households who jointly learned from social networks and extension. The results also suggest heterogeneity concerning the effect of some variables on the outcome variable. For instance, results show that married household heads who did not have access to information on PICS bags from social networks and extension agents were likelier to adopt PICS bags earlier than their married counterparts who obtained information from the two sources. The time to adoption reduces with the size of the household, suggesting the importance of labor in adopting improved postharvest technologies. The household size is usually a proxy for family labor endowments, especially in developing countries. 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 in the social learning and extension equations while increasing the time for those who jointly access both. The results align with those of Manda et al. (2020) and Dadi et al. (2004b) regarding the importance of livestock in technology adoption. As expected, land ownership minimizes the time to adoption.

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. Consistent with similar studies (e.g., Gitonga et al., 2013), having a bank account increases the adoption rate. The coefficient on aflatoxin awareness has the expected sign in the equation for households that didn't access information from social networks and extension agents. 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).

Overall, the variables capturing the transaction costs, i.e., distance to the village, district, 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 and Kongwa 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 postharvest technologies such as PICS bags.

**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 reported in parenthesis. ** p<0.05, ** p<0.01, *** p<0.001*

### 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 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.

**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*** (0.575) | 51 |
| $S_0$ $E_1$ | | -2.126*** (0.473) | 49 |
| $S_1$ $E_1$ | | -2.626*** (0.685) | 61 |

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

Note: Cluster robust standard errors reported in parenthesis. ** p<0.05, ** p<0.01, *** p<0.001*

### 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.

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 (increases) the time to adoption. Results from the two models suggest that the time to adoption by households who jointly learned from social networks and extension agents was more likely to reduce by 59% and 71%, respectively, compared to those who did not know about PICS bags from the two information channels. This speed of adoption is much higher than that if the household were to learn from only the extension agents (42% and 63%) or social networks (21%). 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.

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

| Variable | OLS | COX | Survival time |
|---|---|---|---|
| $S_1$ $E_0$ | -0.119 | $0.213^{**}$ | 0.188 |
| | (0.150) | (0.095) | (0.134) |

| | | | |
|---|---|---|---|
| $S_0 E_1$ | -0.680** | 0.445*** | 0.629*** |
| | (0.274) | (0.167) | (0.239) |
| $S_1 E_1$ | -0.729* | 0.588*** | 0.708** |
| | (0.364) | (0.188) | (0.300) |
| Sex | 0.246** | -0.252** | -0.323** |
| | (0.099) | (0.102) | (0.135) |
| Marital status | -0.149 | 0.186 | 0.233 |
| | (0.167) | (0.155) | (0.183) |
| Household size | -0.028 | 0.014 | 0.027 |
| | (0.030) | (0.022) | (0.033) |
| Education | -0.009 | 0.002 | 0.001 |
| | (0.013) | (0.007) | (0.012) |
| Livestock | 0.003*** | -0.002*** | -0.002*** |
| | (0.001) | (0.000) | (0.001) |
| Land | -0.048 | 0.048*** | 0.063*** |
| | (0.029) | (0.018) | (0.022) |
| Years in village | 0.004 | -0.002 | -0.006 |
| | (0.004) | (0.002) | (0.004) |
| Credit | -0.626*** | 0.497*** | 0.792*** |
| | (0.123) | (0.061) | (0.087) |
| M-Pesa account | 0.058 | 0.170* | 0.113 |
| | (0.094) | (0.098) | (0.108) |
| Savings account | -0.152 | 0.221** | 0.192 |
| | (0.197) | (0.090) | (0.187) |
| Aware of aflatoxin | 0.168 | 0.033 | 0.008 |
| | (0.212) | (0.111) | (0.165) |
| Leadership | 0.101 | 0.017 | -0.028 |
| | (0.093) | (0.067) | (0.079) |
| Ln District market | 0.054 | -0.040 | -0.053 |
| | (0.060) | (0.038) | (0.060) |
| Ln Village market | 0.091 | -0.038 | -0.023 |
| | (0.133) | (0.061) | (0.091) |
| Ln PICS bag market | 0.056 | -0.037 | -0.073 |
| | (0.063) | (0.038) | (0.058) |

| | | | |
|---|---|---|---|
| Ln Extension office | -0.061 | 0.039 | 0.042 |
| | (0.065) | (0.033) | (0.059) |
| Babati district | -0.434*** | 0.183** | 0.402*** |
| | (0.092) | (0.072) | (0.105) |
| Kilolo district | -0.363** | 0.008 | 0.166 |
| | (0.157) | (0.135) | (0.189) |
| Kongwa district | -0.394** | -0.180** | 0.105 |
| | (0.130) | (0.080) | (0.110) |
| Constant | 1.908** | | -1.289 |
| | (0.601) | | (0.843) |
| Observations | 429 | 429 | 429 |

Note: Cluster robust standard errors reported in parenthesis. ** $p<0.05$, ** $p<0.01$, *** $p<0.001$*

### 4.4 Laplace regression quantile survival effects

The violin plots presented in Figure 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 (Figure 3 and Figure 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 (10$^{th}$) quantile includes households with the fastest speed of adoption, while the opposite is true for the farmers in the 90$^{th}$ 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.

**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<0.05, ** p<0.01, *** p<0.001*

## 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 potentially 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 adoption dynamics. 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 to adopt PICS bags in Tanzania. This paper contributes to the empirical literature in this area by examining the interdependent impacts of learning from friends/relatives and extension agents on the speed of PICS bag 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 sources (61%) than from the individual sources. This indicates that these sources 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 the 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. Seeing that PICS bags are 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 isolate the impact of social and extension learning rigorously, a significant limitation of our study is the definition of social learning. Future studies could 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.

**References**

Abass, A.B., Ndunguru, G., Mamiro, P., Alenkhe, B., Mlingi, N., Bekunda, M., 2014. Postharvest food losses in a maize-based farming system of semi-arid savannah area of Tanzania. J. Stored Prod. Res. 57, 49–57. https://doi.org/10.1016/j.jspr.2013.12.004

Abdulai, A., Huffman, W.E., 2005. The diffusion of new agricultural technologies: The case of crossbred-cow technology in Tanzania. Am. J. Agric. Econ. 87, 645–659.

Affognon, H., Mutungi, C., Sanginga, P., Borgemeister, C., 2015. Unpacking postharvest losses in sub-Saharan Africa: A Meta-Analysis. World Dev. 66, 49–68. https://doi.org/10.1016/j.worlddev.2014.08.002

Alcon, F., de Miguel, M.D., Burton, M., 2011. Duration analysis of adoption of drip irrigation technology in southeastern Spain. Technol. Forecast. Soc. Change 78, 991–1001. https://doi.org/10.1016/j.techfore.2011.02.001

An, H., Butler, L.J., 2012. A Discrete-Time Duration Analysis of Technology Disadoption: The Case of rbST in California. Can. J. Agric. Econ. 60, 495–515. https://doi.org/10.1111/j.1744-7976.2012.01255.x

Baoua, I.B., Amadou, L., Ousmane, B., Baributsa, D., Murdock, L.L., 2014. PICS bags for postharvest storage of maize grain in West Africa. J. Stored Prod. Res. 58, 20–28. https://doi.org/10.1016/j.jspr.2014.03.001

Beyene, A.D., Kassie, M., 2015. Speed of adoption of improved maize varieties in Tanzania: An application of duration analysis. Technol. Forecast. Soc. Change 96, 298–307. https://doi.org/10.1016/j.techfore.2015.04.007

Beyerlein, A., 2014. Quantile regression - Opportunities and challenges from a user's perspective. Am. J. Epidemiol. 180, 330–331. https://doi.org/10.1093/aje/kwu178

Bottai, M., Orsini, N., 2013. A command for Laplace regression. Stata J. 13, 302–314. https://doi.org/10.1177/1536867x1301300204

Bottai, M., Zhang, J., 2010. Laplace regression with censored data. Biometrical J. 52, 487–503. https://doi.org/10.1002/bimj.200900310

Canales, E., Bergtold, J.S., Williams, J.R., 2020. Conservation practice complementarity and timing of on-farm adoption. Agric. Econ. (United Kingdom) 51, 777–792. https://doi.org/10.1111/agec.12591

Cattaneo, M.D., 2010. Efficient semiparametric estimation of multivalued treatment effects under ignorability. J. Econom. 155, 138–154. https://doi.org/10.1016/j.jeconom.2009.09.023

Channa, H., Chen, A.Z., Pina, P., Ricker-Gilbert, J., Stein, D., 2019. What drives smallholder farmers' willingness to pay for a new farm technology? Evidence from an experimental auction in Kenya. Food Policy 85, 64–71. https://doi.org/10.1016/j.foodpol.2019.03.005

Channa, H., Jacob, R.-G., Feleke, S., Abdoulaye, T., 2022. Overcoming smallholder farmers' post-harvest constraints through harvest loans and storage technology: Insights from a randomized controlled trial in Tanzania. J. Dev. Econ. https://doi.org/https://doi.org/10.1016/j.jdeveco.2022.102851

Chigoverah, A.A., Mvumi, B.M., 2016. Efficacy of metal silos and hermetic bags against stored-maize insect pests under simulated smallholder farmer conditions. J. Stored Prod. Res. 69, 179–189. https://doi.org/10.1016/j.jspr.2016.08.004

Dadi, L., Burton, M., Ozanne, A., 2004a. Duration analysis of technological adoption in Ethiopian agriculture. J. Agric. Econ. 55, 613–631.

Dadi, L., Burton, M., Ozanne, A., 2004b. Duration Analysis of Technological Adoption in Ethiopian Agriculture. J. Agric. Econ. 55, 613–631.

De Groote, H., Kimenju, S.C., Likhayo, P., Kanampiu, F., Tefera, T., Hellin, J., 2013. Effectiveness of hermetic systems in controlling maize storage pests in Kenya. J. Stored Prod. Res. 53, 27–36. https://doi.org/10.1016/j.jspr.2013.01.001

Euler, M., Schwarze, S., Siregar, H., Qaim, M., 2016. Oil Palm Expansion among Smallholder Farmers in Sumatra, Indonesia. J. Agric. Econ. https://doi.org/10.1111/1477-9552.12163

Frölich, M., Melly, B., 2013. Unconditional Quantile Treatment Effects Under Endogeneity. J. Bus. Econ. Stat. 31, 346–357. https://doi.org/10.1080/07350015.2013.803869

Genius, M., Koundouri, P., Nauges, C., Tzouvelekas, V., 2013. Information Transmission in Irrigation Technology Adoption and Diffusion: Social Learning, Extension Services, and Spatial Effects. Am. J. Agric. Econ. https://doi.org/10.1093/ajae/aat054

Gitonga, Z.M., De Groote, H., Kassie, M., Tefera, T., 2013. Impact of metal silos on households' maize storage, storage losses and food security: An application of a propensity score matching. Food Policy 43, 44–55. https://doi.org/10.1016/j.foodpol.2013.08.005

Jabbar, M. A.,1998. *Adoption pathways for new agricultural technologies: An approach and an application to Vertisol management technology in Ethiopia* (Vol. 23). ILRI

Kadjo, D., Ricker-Gilbert, J., Alexander, C., 2016. Estimating Price Discounts for Low-Quality Maize in sub-Saharan Africa: Evidence from Benin. World Dev. 77, 115–128. https://doi.org/10.1016/j.worlddev.2015.08.004

Kassie, M., Jaleta, M., Shiferaw, B., Mmbando, F., Mekuria, M., 2013. Adoption of interrelated sustainable agricultural practices in smallholder systems: Evidence from rural Tanzania. Technol. Forecast. Soc. Change 80, 525–540. https://doi.org/10.1016/j.techfore.2012.08.007

Khataza, R.R.B., Doole, G.J., Kragt, M.E., Hailu, A., 2018. Information acquisition, learning and the adoption of conservation agriculture in Malawi: A discrete-time duration analysis. Technol. Forecast. Soc. Change 132, 299–307. https://doi.org/10.1016/j.techfore.2018.02.015

Kotu, B.H., Alene, A., Manyong, V., Hoeschle-Zeledon, I., Larbi, A., 2017. Adoption and impacts of sustainable intensification practices in Ghana. Int. J. Agric. Sustain. 15, 539–554. https://doi.org/10.1080/14735903.2017.1369619

Krishnan, P., Patnam, M., 2013. Neighbors and Extension Agents in Ethiopia: Who Matters More for Technology Adoption? Am. J. Agric. Econ. https://doi.org/10.1093/ajae/aat017

Maertens, A., Barrett, C.B., 2013. Measuring social networks' effects on agricultural technology adoption. Am. J. Agric. Econ. 95, 353–359. https://doi.org/10.1093/ajae/aas049

Manda, J., Azzarri, C., Feleke, S., Kotu, B., Claessens, L., Bekunda, M., 2021. Welfare impacts of smallholder farmers' participation in multiple output markets: Empirical evidence from Tanzania. PLoS One 16, 1–20. https://doi.org/10.1371/journal.pone.0250848

Manda, J., Khonje, M.G., Alene, A.D., Tufa, A.H., Abdoulaye, T., Mutenje, M., Setimela, P., Manyong, V., 2020. Does cooperative membership increase and accelerate agricultural technology adoption? Empirical evidence from Zambia. Technol. Forecast. Soc. Change 158, 120160. https://doi.org/10.1016/j.techfore.2020.120160

Miguel A., H., 2010. The Hazards of Hazard Ratios. Epidemiology 23, 13–15. https://doi.org/10.1097/EDE.0b013e3181c1ea43.

Montes de Oca Munguia, O., Pannell, D.J., Llewellyn, R., Stahlmann-Brown, P., 2021. Adoption pathway analysis: Representing the dynamics and diversity of adoption for agricultural practices. Agric. Syst. 191, 103173. https://doi.org/10.1016/j.agsy.2021.103173

Mutungi, C., Affognon, H., 2013. Fighting food losses in Tanzania: The way forward for postharvest research and innovations. *ICIPE policy brief; no. 3/13*. https://idl-bnc-idrc.dspacedirect.org/handle/10625/52219 (last accessed: 30 May 2022).

Mutungi, C., Chamwilambo, M., Masanja, S., Massam, C., Wayda, P., Tungu, J., Gaspar, A., Bekunda, M., Abass, A., 2020. Quality and storability of common beans in small-holders farm stores in Northern Tanzania: A multivariate analysis of agro-location, variety, and storage method effects. Journal of Stored Products Research 89, 101723. https://doi.org/10.1016/j.jspr.2020.101723

Nazli, H., Smale, M., 2016. Dynamics of variety change on wheat farms in Pakistan: A duration analysis. Food Policy 59, 24–33. https://doi.org/10.1016/j.foodpol.2015.12.009

Njoroge, A.W., Affognon, H.D., Mutungi, C.M., Manono, J., Lamuka, P.O., Murdock, L.L., 2014. Triple bag hermetic storage delivers a lethal punch to Prostephanus truncatus (Horn) (Coleoptera: Bostrichidae) in stored maize. J. Stored Prod. Res. 58, 12–19. https://doi.org/10.1016/j.jspr.2014.02.005

Ng'ang'a, J., Mutungi, C.M., Imathiu, S., Affognon, H.D., 2016. Effect of triple-layer hermetic bagging on mould infection and aflatoxin contamination of maize during multi-month on-farm storage in Kenya. Journal of Stored Products Research 69, 119-128.

Omotilewa, O.J., Ricker-Gilbert, J., Ainembabazi, J.H., 2019. Subsidies for Agricultural Technology Adoption: Evidence from a Randomized Experiment with Improved Grain Storage Bags in

Uganda. Am. J. Agric. Econ. 101, 753–772. https://doi.org/10.1093/ajae/aay108

Portnoy, S., 2003. Censored Regression Quantiles. J. Am. Stat. Assoc. 98, 1001–1012. https://doi.org/10.1198/016214503000000954

Rogers EM. 1995., Diffusion of Innovations, 4th edn. Free Press: New York

Sheahan, M., Barrett, C.B., 2017. Food loss and waste in Sub-Saharan Africa: A critical review. Food Policy 70, 1–12. https://doi.org/10.1016/j.foodpol.2017.03.012

Smale, M., Assima, A., Kergna, A., Thériault, V., Weltzien, E., 2018. Farm family effects of adopting improved and hybrid sorghum seed in the Sudan Savanna of West Africa. Food Policy 74, 162–171. https://doi.org/10.1016/j.foodpol.2018.01.001

Stensrud, M.J., Aalen, J.M., Aalen, O.O., Valberg, M., 2019. Limitations of hazard ratios in clinical trials. Eur. Heart J. 40, 1378–1383. https://doi.org/10.1093/eurheartj/ehy770

Sudini, H., Ranga Rao, G. V., Gowda, C.L.L., Chandrika, R., Margam, V., Rathore, A., Murdock, L.L., 2015. Purdue Improved Crop Storage (PICS) bags for safe storage of groundnuts. J. Stored Prod. Res. 64, 133–138. https://doi.org/10.1016/j.jspr.2014.09.002

Tesfaye, W., Tirivayi, N., 2018. The impacts of postharvest storage innovations on food security and welfare in Ethiopia. Food Policy 75, 52–67. https://doi.org/10.1016/j.foodpol.2018.01.004

Vowotor, K.A., Meikle, W.G., Ayertey, J.N., Markham, R.H., 2005. Distribution of and association between the larger grain borer Prostephanus truncatus (Horn) (Coleoptera: Bostrichidae) and the maize weevil Sitophilus zeamais Motschulsky (Coleoptera: Curculionidae) in maize stores. J. Stored Prod. Res. 41, 498–512. https://doi.org/10.1016/j.jspr.2004.08.002

Wang, H.J., Wang, L., 2009. Locally weighted censored quantile regression. J. Am. Stat. Assoc. 104, 1117–1128. https://doi.org/10.1198/jasa.2009.tm08230

World Bank, 2011. Missing food: the case of postharvest grain losses in sub-Saharan Africa, The World Bank. Washington, DC. ©.

Wossen, T., Abdoulaye, T., Alene, A., Haile, M.G., Feleke, S., Olanrewaju, A., Manyong, V., 2017. Impacts of extension access and cooperative membership on technology adoption and household welfare. J. Rural Stud. 54, 223–233. https://doi.org/10.1016/j.jrurstud.2017.06.022

Yigezu, Y.A., Mugera, A., El-Shater, T., Aw-Hassan, A., Piggin, C., Haddad, A., Khalil, Y., Loss, S., 2018. Enhancing adoption of agricultural technologies requiring high initial investment among smallholders. Technol. Forecast. Soc. Change 134, 199–206. https://doi.org/10.1016/j.techfore.2018.06.006

## Appendix

**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 |

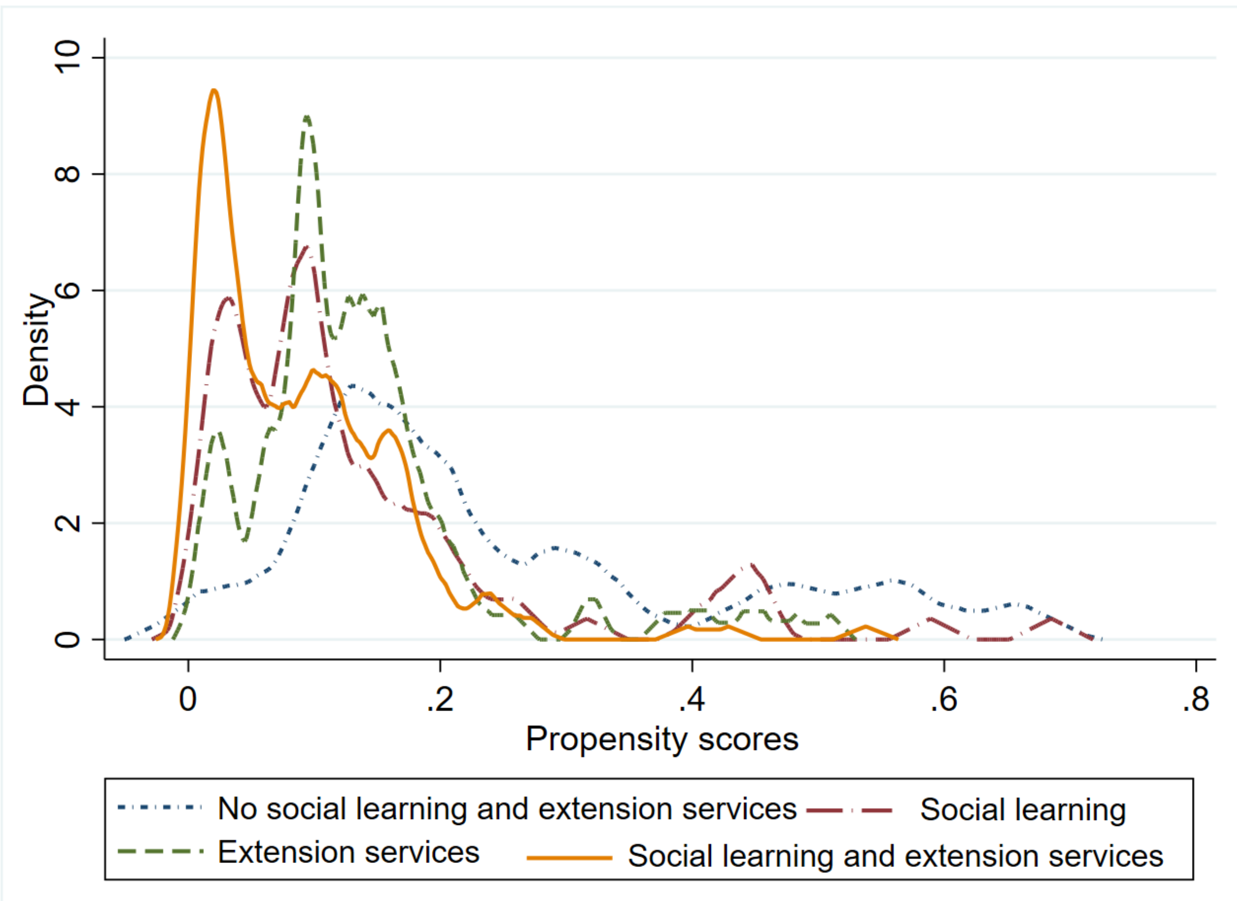


**Figure A1: Balanced plots for the time to adoption by social and extension learning**.

**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 reported in parenthesis. ** p<0.05, ** p<0.01, *** p<0.001*

**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***<br>(0.991) | |
| $S_1$ $E_0$ | | -1.930*<br>(1.027) |
| $S_0$ $E_1$ | | -2.101**<br>(0.823) |
| $S_1$ $E_1$ | | -2.564**<br>(1.172) |

Note: Cluster robust standard errors reported in parenthesis. ** p<0.05, ** p<0.01, *** p<0.001*