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Adoption of *Zai* technology for soil fertility management: evidence from Upper East region, Ghana

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Abstract

Zai is a conventional soil rehabilitation management practice where organic matter is buried in a small pit to help restore fertility and conserve water in the soil. However, adoption of this environmentally-friendly technology is low. This study makes two key contributions. First, it identifies the determinants of adoption and intensity of adoption of *Zai* technology for soil fertility management. Second, it performs diagnostic tests to show that Cragg's double-hurdle as compared to the Heckman and the standard Tobit regression models is the best econometric approach to identify factors influencing farmers' decision to adopt and the extent of adoption of the *Zai* in the Upper East region, Ghana. Results from the Cragg's double-hurdle model revealed that different set of variables affect the probability and the intensity of adoption of *Zai* technology. The paper concludes that farm households should be encouraged to engage in non-farm economic activities to complement their farm income and enhance the purchase of productive farm inputs. Moreover, farm-level policies oriented towards increasing access to agricultural extension services, credit facilities, and the facilitation of farmer groups are essential to improving the adoption of farm innovations such as the *Zai* technology.

Keywords: Adoption, Double-hurdle model, Heckman two-stage model, Intensity of adoption, Zai technology

1 Introduction

The World population is projected to be more than 9 billion by 2050, which is expected to increase the global food demand by 70% between 2005 and 2050 (Nazziwa-Nviiri et al. 2017). Most of these increases are expected to come from developing countries of which Ghana is no exception (United Nations 2011; Alexandratos and Bruinsma 2012). This situation would put upward pressure on agricultural land which is limited by the law of diminishing marginal returns. Hence, identifying, promoting and adoption of sustainable farm technologies are crucial to increase food supply and to address the challenges of environmental degradation. Simtowe et al. (2011) indicated that the adoption of sustainable agricultural technologies remains the route through which developing nations could combat poverty and attain food security.

Conservation agriculture (CA) has been one of the techniques introduced to help mitigate depletion of soil nutrients, conserve water, minimize soil erosion, reduce land degradation and boost farm productivity (Halbrendt et al. 2014). CF was initially introduced in the United States of America (USA) and other developed economies for large-scale farmers. However, it is now implemented in many developing economies especially in Sub-Saharan African mostly by international donor agencies (Knowler and Bradshaw 2007; Giller et al. 2009; Mazvimavi 2011). Fundamentally, CA includes minimum tillage, crop rotation and organic soil cover (FAO 2012). Minimum tillage minimizes the risk of land degradation and retains the soil structure by reducing the intensity of soil disturbance. Tiwari et al. (2009) indicated that minimum tillage reduces both runoff and soil loss. In the US, about 35% of the total land area was cultivated with minimum tillage in the 1980s due to its ability to combat soil erosion (Haggblade and Tembo 2003). Intercropping, particularly with leguminous crops like soybean, improves soil fertility through the addition of soil organic matter, soil cover, and nitrogen fixation. There are extant of previous and recent literature (see Ajayi et al. 2003, 2007; Arslan and Taylor 2009; Mazvimavi 2011; Arslana et al. 2014) on the adoption of conservation practices. The CA has primarily been motivated by the need to understand farmers' decisions to adopt sustainable agrarian techniques for rural development. Most of these studies on the adoption of CA, mainly as promoted in Ghana and other developing countries, focus on CA as a package. This consists of the following: reduced tillage or zero tillage, no burning (leaving crop residue on the field), rotation of cereals with legumes, intercropping with legumes, planting of soil cover, and dry season land preparation (CFU 2007; Arslana et al. 2014). Nevertheless, there is a traditional farming technique that was practiced after the exceptional drought of the 1970s (Abdo 2014). This conventional farming practice was considered as a form of conservation agriculture for soil fertility management, the "*Zai*" pit system, popularly known as the *Zai* technology.

The *Zai* technology was developed by farmers in Burkina-Faso in the early 1960s (Reij et al. 2009). Since then, the approach has widely been promoted and practiced in Burkina-Faso, Mali, and Niger (Sawadogo et al. 2001). For instance, in 1984, a renowned farmer named *Yacouba Sawadogo* who significantly contributed to the invention of the technology began organizing semi-annual market days to promote the *Zai* planting pits (Motis et al. 2013). In 1992, another farmer named *Ousseni Zoromé* started a "*Zai* school," training local farmers about this traditional technology. Motis et al. (2013) revealed that, by 2001, *Zoromé's* network comprised more than 20 schools and 1000 members. Ali Ouedraogo also used a student–teacher procedure to train farmers who needed assistance in implementing this technology (Ouedraogo and Sawadogo 2001; Sawadogo et al. 2001). Through this knowledge exchange, the technology spread beyond Burkina-Faso to other countries like Mali, Niger and Ghana, where NGOs such as Oxfam and World Vision are currently promoting the technology in most of these countries (Reij et al. 2009). This conventional farm technology is designed to rehabilitate degraded lands, conserve soil moisture and improve farm yield.

Zai is the term farmers in Burkina-Faso coined to refer to small planting pits of about 20–30 cm in width, 10–20 cm deep, and filled with manure. In English, terms such as "planting pockets", "planting basins," "micro-pits," and "small water harvesting pits" are used to describe the *Zai* technology. The pits are spaced 70–80 cm apart resulting in about 10,000 holes per hectare. Hence, the *Zai* technology refers to small planting pits in which organic matter (manure, compost or dry biomass) is buried before planting the seed in those pits. The addition of organic matter improves infiltration and increases soil nutrient making degraded land available again for cultivation. The organic matter buried in the soil attracts termites and other soil insects, which help in maintaining soil structure. When maize or millet is planted in the pit, the seedlings are protected from wind damage. The *Zai* pits can hold water over 500% of the water holding capacity of the soil (Danjuma and Mohammed 2015). Thus, *Zai* is an indigenous-based technology used to manage the fertility of poor soils, particularly in drought conditions. The success of this technology during the period of drought in the 1970s reduced the high level of emigration since many were abandoning their land because of low yield (Reij et al. 2009). The technology was one of the breakthroughs in that era which led to its adoption in other Sahelian countries that receive relatively low levels of rainfall, e.g., Mali, Niger and the northern part of Ghana.

One of the critical challenges of smallholders in the Northern part of Ghana is infertile, dry, fragile, relatively low and highly variable rainfall leading to farmers' inability to produce enough to feed the family and generate much-needed incomes. As an effort to address these challenges, the Food Security and Environmental Facility (FSEF) unit in the Garu–Tempane Presbyterian Agricultural Station (PAS-G) introduced the *Zai* technology to farmers in the Garu–Tempane district[1] and Binduri district.[2] However, the adoption the technology has been low in spite of its diffusion. Although Kohli and Singh (1997) stated that imperfect information, risks, institution, and human capital are significant constraints to the adoption of improved agricultural technologies; empirical evidence has proven that technologies vary in forms, and hence, there are changing factors that influence the adoption and adoption intensities of those technologies (Uaiene 2006). Assessing adoption and use intensity of such a drought-tolerant and yield-enhancing technology may serve as an empirical guide to farm-level programmes' design and implementations in areas of agrarian practices and sustainable development.

The decision of adoption is assumed to be two processes, the choice of whether to adopt or not (binary, coded as 1 for adoption, 0 otherwise), and the extent of adoption (continuous decision on the quantities or level of applications). These two-decision processes could be joint or separate. However, some studies (Gregory and Sewando 2013; Kehinde and Adeyemo 2017) used logit or probit to explain factors influencing the probability of adoption. Many other studies (Teklewold et al. 2006; Obuobisa-Darko 2015) in the adoption of agrarian studies have used Cragg's double-hurdle model with a mere assumption that farmers' decision to adopt and intensity of adoption is separate without any econometric test. On the other hand, studies such as Idrisa et al. (2012) and Danso-Abbeam and Baiyegunhi (2017) assumed that adoption and intensity of adoption are joint decisions, hence, employed Tobit regression models. These studies have methodological issues that might lead to misleading conclusions on the factors influencing adoption. Assessing the determinants of the likelihood of adoption alone using probit or logit is inappropriate since it does not provide the full understanding of the factors explaining the entire decision process of adoption. Moreover, assuming that the

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[1] Garu–Tempane district is now two separate districts, Garu district and Tempane district, enacted in 2018.

[2] The Zai technology was introduced to the farmers in the Upper East region of Ghana, and Garu, Tempane and Binduri were among the main districts initially used as pilots.

decisions are joint or separate without any econometric test can also be misleading. It is, therefore, essential for studies in farm technology adoption to apply an analysis of separate or joint decisions to help in employing the appropriate procedure to adequately capture the set of factors that influence the two processes. When the right set of factors is captured, we can make applicable policy guidelines. This study, therefore, contributes to the body of knowledge in twofold. First, it seeks to identify the determinants of adoption and adoption intensity of *Zai* technology in the Garu and Tempane districts of the Upper East region, Ghana. Second, it performs a rigorous test on which econometric technique is the best fit for the data. The inclusion of the diagnostic test of whether the two decisions are joint or separate is an enhancement on methodologies in adoption studies in the body of agrarian literature.

2 Methodology

2.1 The study area, sampling and data collection technique

The study was conducted in the Garu–Tempane districts of Ghana, which is now split into Garu and Tempane districts. The two districts cover a total area of 1060.91 square km. The districts are predominantly rural, and the main economic activity in the area is agriculture, with about 95.4% of the households engaged in agriculture (GSS 2014). Maize is the main cereal crop produced in the two districts. A wide array of other crops such as rice, millet, sorghum and soybean are also produced in the area.

A multi-stage sampling technique was followed in collecting the data set for this study. The Garu and Tempane districts were pre-defined because farmers in that area practiced the *Zai* technology. A simple random sampling was used to select 10 communities from each district, and 20 respondents from each community, which gave a total sample size of 400 farm households. The study employed a quantitative structured questionnaire with modules on farm inputs and output, farmers' socioeconomic characteristics, as well as institutional factors.

2.2 Analytical framework

The underlying theoretical framework for this study is the utility maximization theory which states that economic agents like farmers will adopt a given innovation or technology if the satisfaction they get for adopting is higher than their satisfaction for not adopting (Adesina and Seidi 1995). Consider a W^* to be a latent variable which is the difference in utility between adoptionA_1 and non-adoption A_0 expressed mathematically as

$$W^* = A_1 - A_0. \tag{1}$$

The utility maximization theory asserts that a farmer will adopt the technology if $W^* > 0$ and will not adopt if $W^* < 0$. The latent variable W^* which is the net utility is not observed but could be modelled as a function of farmer-specific, institutional variables and other covariates as

$$W^* = \delta h_i + \upsilon_i, \tag{2}$$

where h_i is the vector of explanatory variables, δ the vector of parametric estimates, and υ_i the error term which accounts for unobserved factors that influence the dependent variable and is assumed to have a zero mean and a constant variance.

In a situation where farmers do not adopt or use the *Zai* technology, zero intensity (measured as the quantity of organic matter put in the *Zai* pits per acre) is reported. Zero observations in survey data, mainly, in this case, can be explained in three ways. First, farmers may not be aware of the technology or may be aware but did not adopt for some reasons. The zero values in the former case are called behavioural zeros, whilst that in the latter case is called random zeros as they occur from random events. Second, the zero observations may result from the survey design as questions may be posed to the farmers with regard to the adoption of the technology without first being asked whether they are aware of the technology or not. Finally, zeros observations may also emanate from erroneous reporting.

The conventional approach of handling data with zero observations leading to a censored dependent variable is the standard Tobit regression proposed by Tobin (1958). The Tobit regression model ignores the sources of zeros that may arise from the non-awareness of the technology and assumes that all zero observations may come from random events such as economic and demographic factors (Newman et al. 2003; Martínez-Espiñeira 2006). Thus, the model incorporates all observations, including those censored at zero. Another drawback of the Tobit model is the joint estimation of the probability and intensity of adoption. In this case, the same set of variables explains farmers' decisions to adopt (discrete) and the intensity of adoption (continuous) which may be misleading because the decision might not necessarily be joint (Wiredu et al. 2015). Other studies (Fufa and Hassan 2006) have used Probit and Tobit model to separately estimate the determinants of probability and intensity of adoption creating a situation of double counting (Adesina 1996; Waithaka et al. 2007).

Cragg (1971) modified the Tobit model to overcome the restrictive assumption associated with it by proposing a double-hurdle model to deal with zero observations. Cragg (1971) argues that two hurdles must be overcome to observe positive values. With regard to the acquisition of durable goods, first, the consumer must desire a definite amount, and second, there should be favourable conditions to realize this actual amount.[3] In terms of adoption of the *Zai* technology, a positive outcome can be observed if first a decision whether to adopt or not is made (first hurdle), and second random conditions permit the extent of usage once the adoption decision has been made (second hurdle). Thus, the first hurdle refers to adoption, and the second refers to the intensity of adoption.

Heckman (1979) also proposes a two-step procedure of dealing with zero observations, arguing that an estimation of the intensity of adoption which is the selected sub-sample (censored estimation) may result in sample selection bias. In Heckman estimation procedure, the first step involves a full sample probit estimation of the probability of observing a positive outcome (discrete decision to adopt) whilst the second stage estimates the intensity of adoption conditional on the likelihood of adoption. Heckman two-step model has an added advantage of dealing with the problem of selectivity bias in addition to the issue of separability by imposing the condition of exclusivity in the first step (Heckman 1979).

[3] This is from the original empirical study of Cragg's double-hurdle with application to the demand for durable goods (Cragg's 1971).

Heckman also assumes that different set of variables could be used in the two-step procedure explaining the probability of adoption and intensity of use.

The Heckman model differs from the standard Tobit model in two main ways. First, the Heckman model is a two-stage estimation where the decision to adopt and intensity of adoption are separate whilst the Tobit is a single-stage estimation process where the decision to adopt and extent of adoption are joint. Second, the Heckman permits different sets of variables to be used in both stages of estimation, whilst Tobit uses the same set of variables for the joint decision-making estimation. The Heckman and the double-hurdle are similar in that both recognize the two-stage estimation processes and the use of different explanatory variables in each stage. However, the Heckman, unlike the Cragg's double-hurdle, assumes that there will be no zero observations in the second stage once the first hurdle is crossed. On the contrary, the double-hurdle recognizes the possibility of zero observations in the second stage of the estimation resulting from an individual's deliberate choices or random occurrences. Thus, the double-hurdle model is an improvement on the standard Tobit and the Heckman models also referred to as Tobit type I and Tobit type II models, respectively (Flood and Gråsjö, 1998, 2001).

2.3 Empirical estimation

As earlier indicated, the decision to adopt the *Zai* technology is in two stages, first is the discrete choice where a farmer decides whether to adopt the *Zai* technology or not and the second is the continuous decision regarding the intensity of adoption (Nwangi and Kariuki 2015). Following Mal et al. (2012), Yirga and Hassan (2013) and Wiredu et al. (2015), the study conducts a diagnostic test to check which of the three models (Tobit, Cragg's double-hurdle, and Heckman two-stage) best fit the data by the use of likelihood ratio test. The test involves the estimation of probit, truncated and Tobit regression models, as shown in Eqs. (3), (4) and (5) below.

$$A_i = \Pr(A_i/A_i^* > 0) = \beta' X_i + \varepsilon_i \tag{3}$$

$$Y_i = E(Y/Y_i^* > 0) = \alpha' Z_i + u_i \tag{4}$$

$$y_i = (\beta' X_i + \varepsilon_i) + (\alpha' Z_i + u_i) = \gamma' R_i + \omega_i. \tag{5}$$

From the above models, the first one represents a probit model with $A = 1$ for *Zai* adopters and $A = 0$ for *Zai* non-adopters, and A^* represents the latent variable for the probability of adoption. The truncated regression is represented by model two (Eq. 4) where Y_i is the adoption intensity (measured as the quantity of organic manure put in the *Zai* pits per acre) and Y_i^* is the latent variable for adoption intensity. The third model (Eq. 5), which is the combination of the first two models, represents the Tobit model. β' and α' are the estimated coefficients of the explanatory variables for the probit and the truncated regression models, respectively, whilst γ' represents the joint estimated coefficient of the two models. X_i, Z_i and R_i are the set of covariates with the associated ε_i, u_i and ω_i as the error terms for the probit, truncated and Tobit models, respectively. The log likelihood ratios are obtained from the three models and used to calculate the Likelihood ratio test statistics, L as follows:

$$L = 2(LR_{prob} + LR_{trun} - LR_{tob}) \tag{6}$$

where LR_{prob}, LR_{trun} and LR_{tob}, respectively are the likelihood ratios of the probit, truncated and Tobit regression models. If the estimated L is greater than χ^2 distribution with the degrees of freedom equal to the number of explanatory variables plus the intercept, then the use of a two-step procedure (Cragg's double-hurdle or Heckman) is justified; otherwise, the Tobit model is appropriate (Mal et al. 2012; Wiredu et al. 2015). The choice between Heckman's two-stage and the Cragg's double-hurdle depends on the presence of selectivity bias.

2.3.1 The Heckman's two-step sample selection model

Heckman's two-step model is one of the most widely used econometric techniques to account for sample selectivity bias and correct for non-randomly selected samples. As the name suggests, it consists of two stages. First, it estimates a probit model for the discrete decision (selection model) to adopt *Zai* technology, and then predicted values of the dependent variable from the probit model are generated and used as a controlling factor called the inverse mills ratio (IMR). The IMR is then used as an additional independent variable in the second step to correct any selectivity biases. The selection equation (Eq. 7)[4] indicating whether farmers adopt the *Zai* or not can be specified as

$$A_i = \beta' X_i + \varepsilon_i \tag{7}$$

where are A_i, β, X_i and ε_i are defined earlier. The second stage estimates intensity of *Zai* adoption (Y_i) through an OLS estimator. Y_i is observed if $A_i > 0$ as indicated in Eqs. (3) or (7). The equation for the second stage is specified as

$$E(Y_i/A_i = 1, Z_i) = \alpha' Z_i + E(u_i/A_i = 1) = \alpha' Z_i + E(u_i/\varepsilon_i > \beta' X_i). \tag{8}$$

In Eq. (8), α are the sets of coefficient estimates of the explanatory variables (Z_i) and u_i is the error term. Let ρ denote the correlations between the error terms of Eqs. (7) and (8). If the error terms have a bivariate normal distribution, according to Greene (2012), the expected value of u_i conditional on ε_i is given as

$$E(u_i/\varepsilon_i) > \beta' X_i = \rho \sigma_u \sigma_\varepsilon \left[\frac{\varphi(\beta' X_i)}{\varphi(\beta' X_i)} \right], \tag{9}$$

where σ_ε and σ_u are the error variances of the probit and OLS estimations, respectively. In estimating the selection equation with the probit model, σ_ε is assumed to be equal to 1 (Greene 2012). The terms in the bracket at the right-hand side of Eq. (9) is the correction factor called the IMR denoted by λ. It is given by the ratio of the normal density function ϕ to that of the cumulative function φ. Inserting the IMR (λ) into Eq. (8) controls for any selectivity bias and the outcome equation then becomes

$$E(Y_i/A_i = 1, Z_i) = \alpha' Z_i + \rho \sigma_{u_i} \lambda_i \tag{10}$$

The coefficient of the IMR is the error covariance and if significant indicates the presence of selectivity bias (Cameron and Trivedi 2010). Thus, a significant IMR suggests that the intensity of *Zai* adoption depends on the discrete decision to adopt (Marchenko and Genton 2012) represented by the probit model in the first step. The condition

[4] Note that Eq. 7 is same as the probit model in Eq. 3.

Table 1 Definition and summary statistics of the explanatory variables used in the analysis

Variables	Description	Mean	SD
Dependent variables			
Zai technology	1 = if farm household practices *Zai* technology	0.45	
Farm size under *Zai*	Farm size allocated to *Zai* technology	1.68	1.36
Intensity of *Zai* technology	Quantity of organic manure applied in *Zai* per acre (kg)	44.08	32.14
Independent variables			
Farmer characteristics			
Sex	1 = if respondent is a male	0.67	
Age	Age of the respondent in years	43.83	14.36
Marital status	1 = if respondent is married	0.83	
Household size	Number of persons in the household (count)	9.87	5.24
Educational attainment	Number of years spent in formal education	5.57	4.10
Economic factors			
Farm size	Farm size allocated to other crops in acres	3.69	2.60
Non-farm income	1 = if respondent engages in any non-farm activity	0.41	
Hired labour	Quantity of labourers hired on *Zai* farm in person-days per cropping season	40.67	23.56
Institutional factors			
Extension contacts	1 = if respondent received extension services	0.53	–
Access to credit	1 = if respondent received cash or input credit	0.40	–
Demonstration farms	1 = if respondent visited demonstration farms	0.26	–
Membership of FBOs	1 = if respondent is a member of a Farmer-based Organization (FBOs)	0.25	–
Membership of VSLA	1 = if household is a member of Village Savings and Loans Association (VSLA)	0.41	–

SD denotes standard deviations

of selectivity bias, which is ignored in the Cragg's model, justifies the use of Heckman's over Cragg's model. However, if there is no sample selectivity bias, then Cragg's model becomes a simple approach for estimating the two-step model. In Cragg's model, the second step is also a truncated regression model without the generation of the IMR. The second step of the Cragg's model is the one specified in Eq. (4), which can be reproduced here as

$$Y_i = E(Y_i/Y_i^*) = \alpha' Z_i + u_i. \tag{11}$$

The variables as defined earlier.

3 Results and discussions

3.1 Descriptive statistics of socio-economic variables

The study followed empirical literature on adoption studies such as Danso-Abbeam and Baiyegunhi (2017), Awotide et al. (2014), Uaiene (2006), amongst others, to select the farmer-specific, economic and institutional factors that have potential influence on *Zai* technology adoption and intensity of adoption. The description of the variables used in the model is presented in Table 1. The dependent variables are the adoption of *Zai* technology and its adoption intensity. About 45% of the respondents interviewed adopted *Zai* technology, whilst the remaining 55% did not adopt. The average farm size allocated to the practice of *Zai* technology was found to be 1.68 acres. The mean statistic further

Table 2 Likelihood ratio test

Models	Likelihood ratio (LR) test				
	Probit	Truncated	Tobit	LR statistic	Decision
Adoption of *Zai* technology	− 103.066	− 88.058	− 88.058	− 206.131***	Two-stage regression preferred to Tobit

*** Significant level at 1%

showed that the average age of the respondents was about 44 years. The majority (67%) of them were males, and as high as 84% of them were married. The average household size was revealed to be about nine members. On average, respondents attained primary education (about 6 years of schooling).

The economic factors taken into consideration were farm size allocated to the production of other crops, engagement in non-farm economic activities, and the quantity of hired labour per cropping season. The average farm size allocated to the production of crops, not under *Zai* technology, was approximately 4 acres. The percentage of farmers engaged in non-farm economic activities was about 41%. The average hired labour used by the sampled farmers in the study area per cropping season was found to be about 40 person-days.

Institutional or policy variables play a critical role in information dissemination, which in turn affects agricultural technology adoption. About 53% of the sampled farm households had access to agricultural extension services, whilst only 40% and 26% received credit and visited demonstration farms, respectively. Moreover, 25% of the sampled farm households are members of FBOs, and 41% are members of VSLAs.

3.2 Determinants of *Zai* technology

In identifying the model that best explains the determinants of farmers' decisions to adopt and extent of adoption of *Zai* technology, two model specification tests were carried out. First, the double-hurdle is tested against the standard Tobit for joint or separate decisions by the use of the LR test, and the results are presented in Table 2. The *LR test* strongly rejects the standard Tobit in favour of the two-stage regression models. Thus, the two-step regression models will provide unbiased and consistent estimates. Moreover, a simple observation of probit and the truncated regression models in Table 3 confirms the rejection of Tobit. Some variables predict the probability of *Zai* adoption, but not the intensity of adoption and vice versa. The rejection of the standard Tobit is also an indication that observations of zero values in the data set cannot be considered to have come from farmers' deliberate choices (corner solutions).

Second, in Table 3, the estimated coefficient of the IMR (λ) is not significant; hence, the null hypothesis that the error terms of the selection equation and the outcome are uncorrelated cannot be rejected. Consequently, there is no selectivity bias, and therefore, the Cragg's double-hurdle model provides a simple, straightforward estimation of probit and truncated regression models. It can, therefore, be concluded that both the standard Tobit and the Heckman two-step models are not adequate to model the determinants of adoption and the intensity of adoption of *Zai* technology in the study area. The *Wald test*

Table 3 Determinants of Zai technology adoption and adoption intensity

Variable	Cragg's Double-Hurdle model			Heckman 2-stage model	
	Stage I		Stage II	Stage I	Stage II
	Coefficient	Marginal effects	Coefficient	Coefficient	Coefficients
Farmer-specific factors					
Age of respondent	0.007 (0.012)	0.003	− 0.005 (0.010)	0.004 (0.012)	− 0.034 (0.009)[a]
Sex of respondent	0.439 (0.217)[b]	0.172	0.321 (0.158)[b]	0.409 (0.228)[b]	0.260 (0.213)
Marital status	0.868 (0.343)[b]	0.302	0.019 (0.384)	0.211 (0.950)[b]	0.866 (0.33)[b]
Household size	− 0.057 (0.022)	0.02	0.043 (0.021)[b]	− 0.015 (0.047)	0.068 (0.024)[b]
Educational attainment	0.031 (0.027)	0.012	0.042 (0.027)[b]	0.045 (0.021)	0.021 (0.027)
Economic factors					
Farm size *non-Zai*	0.052 (0.016)[a]	0.122	0.005 (0.122)[a]	0.086 (0.249)[a]	0.068 (0.057)[a]
Non-farm income	0.025 (0.031)[b]	0.029	0.211 (0.205)[a]	0.024 (0.357)[a]	0.121 (0.342)[b]
Hired labour	0.004 (0.009)	0.004	0.007 (0.003)[c]	0.005 (0.001)	0.021 (0.003)
Institutional factors					
Extension service	0.004 (0.246)[c]	0.142	0.084 (0.167)	0.071 (0.206)[c]	0.005 (0.243)
Field demonstration	0.102 (0.065)	0.039	0.054 (0.034)	0.077 (0.077)	0.139 (0.065)[b]
FBOs membership	0.885 (0.387)	0.316	0.052 (0.275)	0.168 (0.631)	0.893 (0.389)[b]
VSLA membership	0.073 (0.387)[c]	0.288	0.096 (0.515)	0.221 (0.622)	0.001 (0.394)
Access to credit	0.193 (0.367)[c]	0.175	0.108 (0.520)[b]	0.201 (0.641)[b]	0.043 (0.362)
Constant	5.413		1.84	2.67	1.67
IMR (λ)				− 0.191 (1.128)	
Wald χ^2			57.83[a]	54.47[a]	
Rho (ρ)				− 0.232	

a, b and c represents 1%, 5% and 10% significance levels, respectively. The figures in the brackets are the standard errors

for both models is significant at 1% level of significance indicating that the explanatory variables are jointly explaining the variance in the model well.

The coefficient estimates from the Cragg's double-hurdle and the Heckman's two-step models are reported in Table 3. Though the results from Heckman and Cragg's models look similar and can be comparable, the study would focus on the results from the Cragg's model as it is the most appropriate model established by the diagnostic test.

The results showed that sex had a positive and significant effect on the adoption and adoption intensity of *Zai* technology in the study area. Thus, men are more likely to adopt the technology than women. This could be attributed to the difficult nature of the technology where lots of energy is required to dig the pits where men, by their biological make-up can do it better than women. Empirical evidence has also proven that since males are mostly the head of the household, they tend to have access and control over the household resources including the decisions to allocate lands for agricultural activities (Nwangi and Kariuki 2015; Mignouna et al. 2011). For example, a study by Obisesan (2014) found sex to have had a significant and positive influence on the adoption of improved cassava production in Nigeria which was in congruence with that of Lavison (2013) who indicated that male farmers were more likely to adopt organic fertilizer, unlike their female counterparts. Marital status of the respondent was found to have a positive and significant effect on the probability of *Zai* technology adoption, but no effect on the intensity of adoption. This result did not come as a surprise as the married people could easily pool resources together and may also have more considerable active family labour. Household size was significant in explaining the intensity of adoption but redundant concerning the probability of adoption. This could be ascribed to the possible high supply of labour. The results are in line with that of Nwangi and Kariuki (2015) who indicated that larger household size suggests potential labour force. Education was found to be a significant determinant of *Zai* technology adoption, as observed in the first hurdle of the Cragg's model. Mignouna et al. (2011), Lavison (2013) and Namara et al. (2013) indicated that educational attainment increases farmers' ability to obtain, process and use information relevant to the adoption of a new technology.

The farm size owned by the household was found to have a positive and significant effect on the adoption of *Zai* technology. The result is in cognizance with the findings of Nwangi and Kariuki (2015) who indicated that farm size is an essential determinant of agricultural technology adoption. Uaiene et al. (2009) also noted that farmers with large farm size are likely to adopt a new technology as they can afford to devote part of their land to try the technology, unlike those with small farm size. The estimates from Table 3 also show that farmers' engagement in non-farm economic activities has a direct and significant effect on both the probability and the intensity of adoption. Reardon et al. (2007) indicated that non-farm income acts as an important strategy for overcoming credit constraints faced by rural households in many developing countries in adopting improved agricultural technologies. It is also said to act as a substitute for borrowed capital in rural economies where credit markets are either missing or dysfunctional (Ellis and Ade Freeman 2004; Diiro 2013). Moreover, a study by Diiro (2013) in analyzing the impact of non-farm earnings on the intensity of adoption of improved maize varieties and the productivity of maize farming in Uganda revealed a significantly higher adoption intensity and expenditure on purchased inputs amongst households with non-farm income compared to their counterparts without non-farm income.

Per the results of our study, estimates related to the supply-side policy variables such as access to agricultural extension services and credit have positive and significant effects on both the probability and intensity of adoption. These results are similar to those obtained from other studies such as Kassie et al. (2015), Sisay et al. (2015), Mmbando and Baiyegunhi (2016), Danso-Abbeam and Baiyegunhi (2017), amongst others. However, farmers' membership of VSLA is a significant determinant of the likelihood of adoption but insignificant in explaining the intensity of adoption.

4 Conclusions and recommendations

The study has estimated the determinants of the probability of adoption and the extent of adoption of *Zai* technology using 400 farm households from Garu and Tempane districts of the Upper East region, Ghana. The study has shown that discrete decisions of adoption and the extent of adoption could be joint or separate; hence, just assuming that these two decisions are separate or joint without recourse to any diagnostic test may be misleading. This is because a different set of variables may influence adoption and intensity of adoption. The study, therefore, recommends improvements in the methodology of adoption studies in general. The significant findings from this paper revealed that farmer-specific factors (such as sex), economic factors (such as farm size of other food crops, engagement in non-farm income) and institutional factors (access to credit) influence both the probability and intensity of adoption. However, factors such as marital status, access to extension services, and membership of VSLA significantly affect the likelihood of *Zai* technology adoption but have no significant effects on the intensity of adoption. Further, household size, amount of hired labour, and education have a positive and significant influence on the extent of adoption but redundant in explaining the probability of adoption. The results of the study suggest that to boost food crop productivity through improved agrarian technology, access to extension service should be strengthened through adequate provision of logistics, in-house training and recruitment of agents. Farm households should be encouraged to engage in non-farm economic activities in order to complement their farm income and enhance the purchase of productive farm inputs. Finally, farm-level policies oriented towards increasing access to agricultural credit and membership of VSLAs are essential to improving the adoption of farm innovations. Moreover, stakeholders implementing *Zai* technology in the farming communities should pay attention to the variables identified to shape farmers' adoption decisions significantly. This will guide them to make an informed decision regarding the designing and the implementation of the programmes.

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Authors' contributions
GDA conceptualized the study, provided the guidelines for the analysis, and wrote the introduction and the methodology, and made editorial comments to the draft manuscript. GD designed the household survey, supervised the data collection and performed the analysis. DSE discussed the results and wrote the conclusion. All authors read and approved the final manuscript.

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Ethical approval and consent to participate are not applicable for this study.

Conflict of interests
The authors declare that they have no competing interests.

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