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Heterogeneity in returns to agricultural technologies with incomplete diffusion: Evidence from Ghana

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Abstract

In this study, we employ a dynamic treatment effect approach to analyze heterogeneity in returns to farmers at different stages of adoption of a newly introduced inoculant technology, using a recent survey data of 600 soybean farmers from northern Ghana. Although farmers differ in their returns to adoption of new technologies, many empirical studies often fail to account for this heterogeneity. The empirical results reveal that farmers who are at advanced stages of adoption appear to, on average, more than double their yields and farm net returns, suggesting that the inoculant technology may be a game changer in the fight against extreme poverty in the region, where poverty is endemic and crop yields are persistently below the average potential yield target. Our findings further reveal that extension services as well as efficient input and output markets are key to the adoption process, by influencing knowledge acquisition, adoption, and continued adoption. Our findings also show significant impact heterogeneity at each adoption stage, with the long-term benefits of the inoculant technology outweighing its short-term benefits.

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dynamic treatment effect, impact heterogeneity, inoculant technology adoption, multistage decision-making

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1 | INTRODUCTION

Low agricultural productivity and perennial food insecurity are major global concerns facing low-income countries, particularly countries in sub-Saharan Africa (SSA). Central to tackling the problem are increasing crop yields and sustaining gains through the adoption of improved agricultural technologies (Takahashi et al., 2020). Yet the technology adoption rate among farmers in these countries appears to be very low (Macours, 2019; Sheahan & Barrett, 2017; Suri, 2011). While some analysts partly attribute the phenomenon to factors such as lack of information, low education, and credit constraints, others question the empirical and theoretical adoption models used to analyze farmers' adoption decisions (Besley & Case, 1993; Feder et al., 1985; Lindner et al., 1982). In particular, Besley and Case (1993) note that technology adoption is a dynamic process in which farmers make a series of decisions over multiple stages or seasons. Lindner et al. (1982) succinctly summarized the adoption process into three broad categories: *discovery stage*, *evaluation stage*, and *trial stage*. Each stage in the adoption process collects different sets of vital information for the farmer to update subsequent decisions. However, classical studies on technology adoption mostly consider farmers' adoption decisions as static, ignoring the dynamic processes embedded in farmers' decision-making. As a result, important information on farmers' adoption behavior relevant to policy formulation is lost, and their decisions are misinterpreted. Thus, it is not uncommon for analysts to find farmers' adoption decisions at odds with rationality and sometimes counterintuitive (Besley & Case, 1993).

This study departs from the classical approach and analyzes farmers' adoption decisions in a dynamic framework. Previous studies that examined farmers' technology adoption decision-making in a dynamic framework mainly focused on adoption determinants, patterns of diffusion, and intensity of adoption (e.g., Abdulai & Huffman, 2005; Feder & Slade, 1984; Lambrecht et al., 2014; Simtowe et al., 2016), while some studies employed it to explain farmers' learning behavior, risk preferences, and uncertainties (Ghadim & Pannell, 1999). The missing link in the dynamic adoption literature is the impact of adoption on output levels and other welfare indicators, such as yields and farm net returns, which underlie farmers' adoption and continued adoption decisions. These indicators also drive adoption patterns and clarify risks and uncertainties that may surround a given technology (Besley & Case, 1993; Feder et al., 1985). We contribute to the literature by analyzing farmers' adoption decision-making process as a multi-stage decision problem and how adoption impacts on farm outcomes. One in which each stage of adoption is characterized by different margins of payoffs or gains that accrue to farmers at that stage. We apply this approach to analyze farmers' adoption decisions of a new *Rhizobia* inoculant technology among 600 soybean farmers in northern Ghana, considering that farmers' returns from adoption may be heterogeneous and stage dependent.

Few studies in the technology adoption literature have analyzed heterogeneity in returns to adoption of agricultural technologies (Abdul Mumin & Abdulai, 2021; Shahzad & Abdulai, 2021).

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However, adoption at different stages were not considered. As argued by Heckman et al. (2018), individuals differ in their returns to treatment, and failure to account for this heterogeneity can lead to confusion in interpreting the estimated effects of treatment, particularly when the individuals may be at different stages of treatment. In this study, we employ a dynamic treatment effects model to account for heterogeneity in returns to adoption for farmers at different stages of adoption. Thus, we analyze the relationship between the farmers' state of adoption and the final outcomes (which in our case are yields and farm net returns) obtained from adoption. The adoption stages considered in this study include awareness and knowledge acquisition about the inoculant technology, trying the technology, and adopting and continuous adoption of the technology. The inoculant technology is a recently developed agricultural input by research scientists to improve productivity of grain legumes in SSA. The technology exploits the symbiotic relationship of an elite strain of bacteria known as *Bradyrhizobium spp* as an inoculant to enhance nitrogen fixation in legumes. One crop that has received much attention in this process is soybean (see Chibeba et al., 2018; van Heerwaarden et al., 2018). Field experiments of the inoculant show promising results, with a potential to increase average soy grain yield by 20%–29% in African soils (Chibeba et al., 2018). The technology was recently introduced to smallholder farmers in northern Ghana by a number of organizations[1] and their partners working together to improve soybean production in the region. As a newly introduced technology with incomplete diffusion, it is imperative to investigate what factors drive the adoption of the inoculant technology and to what extent information from one stage of adoption decision can influence further adoption decisions in the process, as well as the impact of adoption on yields and farm net returns.

Our findings reveal that farmers who are at advanced stages of adoption appear to, on average, more than double their yields and farm net returns, suggesting that the new inoculant technology has the potential to contribute to poverty reduction in the region, where poverty is endemic and crop yields are below the potential yield target. Our findings further reveal that the long-term effects are much stronger than the short-term effects, conditional on the markets being able to absorb the excess supply that may result from higher yields. Finally, we also found that extension services as well as efficient input and output markets are key to the inoculant adoption process, by influencing knowledge acquisition, adoption, and continued adoption.

The rest of the paper is organized as follows. Sections 2 and 3 present the theoretical framework and empirical specification, respectively, while Sections 4 and 5 present the identification and estimation strategy and the study context, respectively. Section 6 presents the data used in the study, while Section 7 contains our empirical results. Section 8 presents the conclusions and policy implications of the study.

2 | THEORETICAL FRAMEWORK

We assume that farmers are risk neutral and their technology adoption decisions are guided by expected net benefits from adoption (Kleemann & Abdulai, 2013). Farmers' adoption decisions of a new technology are conceptualized as a decision tree consisting of five decision-making nodes along adoption path T (see Figure A1 in Appendix A1). Let N represent a finite adoption decision-making node along the entire adoption path with a finite decision horizon $(\underline{s}, \overline{s})$, where $\underline{s}$ is the lowest adoption state and $\overline{s}$ is the highest-attainable adoption state;$A_n(s)$ be the choice indicator for adoption state s for a farmer at adoption decision-making node n; and $W_n(s)$ be the expected net benefits for a farmer in adoption state s.

In line with Heckman et al. (2016), the farmer's current adoption state s net benefits can be expressed as follows:

$$W(s) = \sum_{n=1}^{N} A_n(s) W_n(s), \tag{1}$$

where $W(s)$ is the current net benefits for a farmer in adoption state s and all other notations remain as defined earlier.

Under autonomy, when the discrete choices made by a decision-maker at the decision-making node are known to the econometrician, the dynamic discrete choice model can be employed to understand the decision-maker's intertemporal behavior and its consequences (Heckman et al., 2016). We assume that the farmer's adoption state decision at any decision-making node is autonomous. A farmer may decide to stop at any adoption state or continue to the next state if the expected net benefits for continuing to the next adoption state are lower than the current adoption state's net benefits. Let $\mathscr{H}(s)$ be the individual farmer's perceived state value of the net benefits for continuing to the next adoption state. The individual farmer's perceived value function for continuing to any adoption state s along the adoption path t can be represented as follows (Heckman et al., 2016):

$$V(\mathscr{H}(s), s) = \max_{A_n(t) \in \text{Å}(s)} E\left[\sum_{t=s}^{\bar{s}} \delta^{t-s} \sum_{n=1}^{N} A_n(t) W_n(t) \,|\, \mathscr{H}(s) \right], \tag{2}$$

where $\text{Å}(s)$ is the set of feasible current and future adoption state choices available to the farmer at the decision-making node, δ is the farmer's assumed discount factor for valuing the perceived net benefits across the decision horizon,[2] and all other notations remain as defined earlier.

The farmer's valuation of the state net benefits from adoption at any adoption decision-making node consists of the current state s benefits and that of the future adoption state $s+1$ benefits if they continue to the next adoption state.[3] To reflect this relationship in the farmer's value function at each decision-making node n, we follow Heckman et al. (2016) and express the state-specific value function in terms of Equations 1 and 2 as follows:

$$V_n(\mathscr{H}(s), s) = W_n(\mathscr{H}(s), s) + \delta E\left[V(\mathscr{H}(s+1), s+1) \,|\, \mathscr{H}(s), A_n(s) = 1 \right], \tag{3}$$

where $W_n(.,.)$ is the farmer's current adoption state s value function and $\delta E[V(.)]$ is the farmer's expected value function if the farmer continues to the next adoption state $s+1$.

However, the expected net benefits from adoption at any state are latent and cannot be observed, but the actual adoption choices made by the farmer can be observed. We set the adoption choice indicator $A_n(s)$ equal to 1 if a farmer at decision node n choses to be in adoption state s, and 0 otherwise.

Based on the state-specific perceived net benefit value function, the farmer's adoption state choice[4] at any decision-making node n can be represented as follows (Heckman et al., 2016):

$$\begin{aligned} &A_n(s) = 1, \text{ if } \left[n = \underset{j \in \{1,\ldots,N\}}{\text{argmax}} \left\{ V_j(\mathscr{H}(s), s) \right\} \right], \\ &A_n(s) = 0, \qquad\qquad \text{otherwise} \end{aligned} \tag{4}$$

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As noted by Heckman et al. (2016, 2018), the specification of the decision rule in Equation 4 differs from conventional decision-making rules in the dynamic discrete choice literature. When no specific choice rule is assumed, it imposes neither rational expectation assumption nor forward-looking behavior on agents at any decision node. Therefore, agents may be myopic, time inconsistent, and subjected to surprises. For instance, it is possible under a myopic decision rule, as inherent in the Bellman's decision rules, for a farmer who obtains negative returns at early stages of adoption to abandon the technology and similarly, under a forward-looking behavior, as inherent in the Euler decision rule, for a farmer to continue to adopt the technology with the expectation of getting higher returns in the long term, despite obtaining negative returns at the early stages of adoption.[5]

Aguirregabiria and Mira (2010) note that farmers at different adoption states differ in both observed and unobserved characteristics (i.e., $s = (x, \epsilon)$), indicating that the farmers' adoption choice decisions as expressed in Equation 4 may be random and subject to shocks. The farmer's optimal choice decision at any adoption state can be expressed in terms of the state-specific variables that enter the farmer's conditional choice probability function (Aguirregabiria & Mira, 2010; Arcidiacono & Ellickson, 2011) as follows :

$$\begin{aligned} p_j\left(a_{ij}|x_{ij},y\right) &= \int I(\delta\left(x_{ij},\varepsilon_{ij};y\right) g\left(\varepsilon_{ij}\right) d\varepsilon_{ij} \\ &= \int I\left\{\underset{j}{\operatorname{argmax}}\left[v_j\left(x_{ij},a_{ij};y\right)+\varepsilon_{ij}\left(a_j\right)\right]=a_{ij}\right\} g\left(\varepsilon_{ij}\right) d\varepsilon_{ij}, \end{aligned} \tag{5}$$

where a_j is the farmer's optimal choice indicator; p_j is the conditional choice probability function of choosing adoption state j; x is a vector of observed characteristic; ϵ is the unobserved state factors that influence state-specific value function (i.e., the error term); y is a parameterized vector of payoffs or outcomes (e.g., yield and farm net returns in our case), consisting of the flow payoff at a particular adoption state (y_j) and the transition state (y_{j+1}) (i.e., $y \equiv \{y_j, y_{j+1}\}$); I is an indicator function; $g(.)$ is the distribution function of the state-specific error term; and other symbols remain as defined earlier.

The expected payoff function for farmers' optimal adoption choice decisions can be approximated (Aguirregabiria & Mira, 2010; Arcidiacono & Ellickson, 2011) as follows:

$$\hat{y} = \underset{j}{\operatorname{argmax}} \sum_{i=1}^{\mathbb{N}} \sum_{j=1}^{N} \left(\ln\left[p_j\left(a_j|x_j;y\right)\right] + \ln\left[f\left(x_{j+1}|x_j,a_j;y_{j+1}\right)\right]\right), \tag{6}$$

where $\hat{y}$ is the expected outcome from optimal adoption choice decision, $\mathbb{N}$ is the number of farmers, $f(.)$ is the state transition probability function, and all other symbols remain as defined earlier.

Equation 6 consists of two additive separable components, that is, the adoption state choice component (i.e., $p_j(.)$) and the state transition component (i.e., $f(.)$). The additive separability assumption enables each of the components to be empirically estimated separately, thus saving computational time and complexity (Arcidiacono & Ellickson, 2011). The following sections provide detailed empirical specifications of each component as separate models.

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3 | EMPIRICAL SPECIFICATIONS

3.1 | Adoption state choice decision

Let Y_i denote the individual farmer's net benefits from soybean production and A_i be the indicator for the farmer's inoculant adoption choice decision. The farmer's expected outcomes from the inoculant adoption choice decision can be expressed as follows:

$$Y_i = \alpha_i + \rho_i A_i + \gamma_i X_i + U_i, \tag{7}$$

where X_i is a vector of observed characteristics (farm- and household-level characteristics), ρ_i and γ_i are vectors of parameters of interest, α_i is a constant, and U_i is an error term.

Conventional static adoption decision analysis often treats A_i as a single binary decision (e.g., Kleemann & Abdulai, 2013). However, farmers tend to evaluate the performance of the technology over many seasons before making final adoption decisions. Therefore, the adoption decision indicator A_i may not be a onetime binary decision but several binary decisions across many seasons or transitions. In this setting, we assume that the farmer's adoption decision follows a dynamic process, one in which the farmer is assumed to make finite adoption decisions in an irreversible sequential order over multiple stages.

Let $\mathcal{J} = \{1, \cdots, \bar{s} - 1\}\ \forall N$ be a set of all possible terminal adoption states, and $S = \{1, \ldots, \bar{s}\}$ denote an ordered set of all stopping states (i.e., all states that a farmer is observed to make a stop during the process), with $\bar{s}$ as the highest-attainable state. A farmer at each node makes a binary decision, to either remain at node $j (j \neq 0)$ or transit to the next node $j + 1 (j \neq j + 1)$ and $j \in \mathcal{J}$. We assume the farmer operates in a time-stationary decision environment, and past choices reveal the farmer's transition decisions. Let D represent a finite set of all possible transition decisions that a farmer can make over the decision horizon $D_j \in \mathrm{D}$, D_s be the farmer's stopping state decision for all $s \in S$, and Q_j be the history of all states the farmer visited and assumed to be binary (i.e., $Q_j = 1$ if the farmer visits a state, otherwise $Q_j = 0$). We fixed[6] $D_j = 0 (D_s \neq 1)$ if a farmer at j does not stop but moves to $j + 1$ and $D_j = 1 (D_s = 1)$ if the farmer stops at state j (Heckman et al., 2016, 2018).

The farmer must make a transition decision, to either remain at j or move from j to $j + 1$. We assume that the net benefits differ from state to state, and the farmer compares the current state benefits to the net benefits of moving to the next state, before making a transition decision. We specify the farmer's transition decision (D_j) as follows:

$$D_j = \left\{ \begin{array}{ll} 0, \text{ if } \mathbf{I_j} \geq 0, j \in I = \{1, \ldots, \bar{s} - 1\} \\ 1, \qquad \text{otherwise} \end{array} \right\} \text{for } Q_j = 1, j \in \mathcal{J} = \{1, \ldots, \bar{s} - 1\}, \tag{8}$$

where $\mathbf{I_j}$ is the indicator of the farmer's perceived state-specific value function for a farmer considering a move from $j (j \neq 0)$ to $j + 1$.

At each adoption state, the perceived value function $\mathbf{I_j}$ is assumed to cross a threshold value for the farmer to move from one state to another. To understand the farmer's choice decision at each adoption state, we specify the empirical state-specific value function $\mathbf{I_j}$ in a separable model as follows (Heckman et al., 2016, 2018):

$$\mathbf{I_j} = \varnothing_j (\boldsymbol{Z}) - \eta_j, j \in \mathcal{J} = \{1, \cdots, \bar{s} - 1\}, \tag{9}$$

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where $\boldsymbol{Z}$ is a vector of observed characteristics that include an instrument for identification not included in X_i and η_j represents the unobserved factors that affect the farmer's transitional ability.

Due to observed and unobserved factors that characterize different adoption transitions, each transition decision that the farmer makes has a range of potential outcomes. By indexing the state-specific potential outcomes as k (where $k \in \boldsymbol{K_s}$ and $\boldsymbol{K_s}$ is a set of all possible outcomes), a farmer at adoption state s potential outcomes from inoculant adoption can be denoted as Y_s^k. The individual farmer's state-specific potential outcomes equation for any adoption state can then be expressed in a separable model as follows (Heckman et al., 2016, 2018):

$$Y_s^k = \tau_s^k(\boldsymbol{X}) + U_s^k,\ k \in \boldsymbol{K_s},\ \mathrm{s} \in S_s, \tag{10}$$

where Y_s^k is the state-specific potential outcome; $\boldsymbol{X}$ is a vector of observed characteristics that determine the outcome at a particular state; τ_s^k is a parameter of interest; and U_s^k is state-specific unobserved factors. Conditional on the number of adoption states that a farmer visits during the transitional process, the observed potential outcome common across all adoption states (Y^k) visited can be expressed in a switching regression framework (Quandt, 1972) as follows:

$$Y^k = \left(\sum_{S\setminus\{\bar{s}\}} D_s Y_s^k\right)\left(1 - D_0\right) + \left(Y_0^k\right) D_0, \tag{11}$$

where D_s is the stopping decision indicator; D_0 (i.e., for $D_s \neq 1$) is the transition decision indicator; Y_s^k is as defined earlier; and Y_0^k is the counterfactual outcome if the farmer decides to remain at the current adoption state.

4 | IMPACT IDENTIFICATION AND ESTIMATION STRATEGY

The identification of dynamic technology adoption decisions must consider heterogeneity in observed and unobserved farmer characteristics (Benhabib et al., 2019; Fagereng et al., 2020; Gabaix et al., 2016). In particular, farmers differ in wealth endowment, which is potentially endogenous to their transitional ability. Let $\boldsymbol{\theta}$ denote the finite dimensional vector of a farmer's unobserved wealth endowments (e.g., financial ability for farm investment) that can be proxied by observables (e.g., household assets, livestock holding, and nonfarm income sources) in a measurement equation. Intuitively, the financial ability of a farmer determines the scale of farm operations and investment in production inputs, thus generating a potential correlation between the farmer's transition decision and the potential outcomes.[7] We respecify both the state-specific value function and the potential outcome equations (Equations 7 and 8, respectively) controlling for unobserved wealth endowment as follows:

$$\mathbf{I_j} = \varnothing_j(\boldsymbol{Z}) + \boldsymbol{\theta}'\lambda_j - v_j, j \in \mathcal{J} = \{1, \ldots, \bar{s} - 1\}, \tag{12}$$

$$Y_s^k = \tau_s^k(\boldsymbol{X}) + \boldsymbol{\theta}'\psi_s^k + \omega_s^k, k \in \boldsymbol{K_s}, s \in S_s, \tag{13}$$

where λ_j and ψ_s^k are the vectors of parameters of interest, respectively; v_j and ω_s^k are the error terms, respectively; and $\boldsymbol{Z}$ and $\boldsymbol{X}$ are as defined previously.

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We assume there could be problems with measurement errors, because $\boldsymbol{\theta}$ is not directly observed but proxied with observable indicators. Let $\mathbf{M}$ be a system of measurement equations that relate a vector of N_M measurement indicators of $\boldsymbol{\theta}$ to Equations 12 and 13. Parsimoniously, the measurement equation $\mathbf{M}$ can be specified as follows (Heckman et al., 2016, 2018):

$$\mathbf{M} = \phi(\boldsymbol{X}, \boldsymbol{\theta}, \boldsymbol{e}) = \begin{pmatrix} M_1 \\ \vdots \\ M_{N_M} \end{pmatrix} = \begin{pmatrix} \Phi_1(X, \theta, e_1) \\ \vdots \\ \Phi_{N_M}(X, \theta, e_{N_M}) \end{pmatrix}, \tag{14}$$

where $\boldsymbol{X}$ is a vector of observed variables, $\boldsymbol{\theta}$ is a vector of endowment factors, and $\boldsymbol{e}$ is a vector of error terms that ensure orthogonality ($\boldsymbol{e} _\, \overline{\|} X, Z, \theta, v, \omega$) with the error terms in Equations 12 and 13, respectively (Heckman et al., 2016, 2018).

By conditioning on ($\boldsymbol{D_i}$, $\boldsymbol{M_i}$, $\boldsymbol{X_i}$,$\boldsymbol{Z_i}$), a parsimonious maximum likelihood function ($\mathscr{L}$)[8] for an individual farmer can be specified as follows:

$$\begin{aligned} \mathscr{L} &= \prod_i f\left(\boldsymbol{Y_i}, \boldsymbol{D_i}, \boldsymbol{M_i} | \boldsymbol{X_i}, \boldsymbol{Z_i}\right) \\ &= \prod_i \int f_Y\left(\boldsymbol{Y_i} | D_i, X_i, Z_i, \theta\right) f_D\left(\boldsymbol{D_i}, \boldsymbol{M_i} | X_i, Z_i, \theta\right) f_M(\boldsymbol{\theta})\, d\boldsymbol{\theta}, \end{aligned} \tag{15}$$

where $f_Y(.)$, $f_D(.)$, and $f_M(.)$ are the probability density functions for the potential outcomes, adoption decision, and measurement equations, respectively, and all other notations remain as defined earlier.

Equation 15 consists of three components, which are estimated simultaneously in a factor structural discrete choice model. The factor model $f_M(.)$ is estimated in the first stage and in the second stage, the adoption decision model $f_D(.)$ is estimated with the inclusion of an instrument (Z) to account for selection bias, and a factor score (θ) is predicted from the measurement model in the first stage to account for unobserved ability or wealth endowment effect on the farmer's adoption decision. In the final stage, the potential outcomes (i.e., both the treated case and the counterfactual case) model $f_Y(.)$ is estimated conditional on the first two stages. The model is estimated using a mixture of normals in a Gauss-Hermite quadrature approach, sampling 10 point grids each time to numerically evaluate the integral in a joint estimation process.[9]

4.1 | Estimation of treatment effects

In this section, we provide the econometric relationship between the treatment and the outcomes. The treatment refers to the various transitional states, while the outcomes are the state-specific benefits. Let T_j^k denote the farmer-specific treatment effect for being at state j. The T_j^k of an individual farmer selected at random from the population of $Q_j = 1$ with characteristics, $\boldsymbol{X} = x$, $\boldsymbol{Z} = z$, $\boldsymbol{\theta} = \overline{\theta}$, making a decision whether to transit from j to $j+1$ or remain at j can be represented as follows:

$$T_j^k = \left(Y^k | \boldsymbol{X} = x, \boldsymbol{Z} = z, \boldsymbol{\theta} = \overline{\theta}, Q_j = 1,\ Fix\, D_j = 0\right) - \left(Y^k | \boldsymbol{X} = x, \boldsymbol{Z} = z,\ \boldsymbol{\theta} = \overline{\theta},\ Q_j = 1,\ Fix\, D_j = 1\right). \tag{16}$$

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Unlike the classical treatment effect models, the individual-level treatment effects can be decomposed into two components. The first component is the direct effect of making a transition from j to $j+1$. For a known population of farmers, the population-level direct average treatment effect (ATE) for farmers at state j, conditional on $(Q_j = 1)$ and integrating over the vector of $\boldsymbol{X} = x, \boldsymbol{Z} = z, \boldsymbol{\theta} = \overline{\theta}$ is obtained as follows:

$$ATE_j^k := \int \dots \int E\left(T_j^k\left[Y^k|\boldsymbol{X}=\boldsymbol{x},\boldsymbol{Z}=\boldsymbol{z},\boldsymbol{\theta}=\overline{\boldsymbol{\theta}}\right]\right) dF_{X,Z,\theta}\left(\boldsymbol{x},\boldsymbol{z},\overline{\theta}|Q_j=1\right). \tag{17}$$

The same procedure is followed to obtain the treatment effect for both treated (ATT) and untreated (ATUT) farmers at each transition state.

The second component is the continuation effect for a farmer going beyond $j+1$ to l (where l is the subsequent states after $j+1$), which evaluates the long-term impact of technology adoption (Heckman et al., 2016, 2018). The continuation effect (C_{j+1}^k) component of the treatment effect is derived by conditioning on $(Q_j = 1)$, of the population of farmers at $j+1$, using the law of iterated expectations as follows[10]:

$$\begin{aligned} E_{X,Z,\theta}\left(C_{j+1}^k\right) = E_{X,Z,\theta}\Bigg[\sum_{l=j+1}^{\bar{s}-1}\Big\{E\left(Y_{l+1}^k - Y_l^k|\boldsymbol{X}=x,\boldsymbol{Z}=z,\boldsymbol{\theta}=\overline{\theta},Q_{l+1}=1,FixQ_{j+1}=1\right) \\ .Pr\left(Q_{l+1}=1|\boldsymbol{X}=x,\boldsymbol{Z}=z,\boldsymbol{\theta}=\overline{\theta},Q_j=1,FixQ_{j+1}=1\right)\Big\}|Q_j=1\Bigg], \end{aligned} \tag{18}$$

where Pr is the transition probability of moving beyond $j+1$ to l (where l is the subsequent states after $j+1$).

The average marginal treatment effect (AMTE), which provides more in depth into the decision-making behavior of a decision-maker, is also obtained as follows:

$$AMTE_j^k := \iiint E\left[T_j^k\left(Y^k|\boldsymbol{X}=x,\boldsymbol{Z}=z,\boldsymbol{\theta}=\overline{\theta}\right)\right] dF_{X,Z,\theta}\left(x,z,\overline{\theta}|Q_j=1,\left|\mathrm{I}_j\right|\leq\varepsilon\right). \tag{19}$$

The economic intuition of the AMTE is that it represents a fair measurement of the ex post gross marginal benefits of moving from one adoption state to the next state for a population of farmers at a decision-making node, who may be indifferent in their transition decision $(|\mathrm{I}_j| \leq \varepsilon)$ (Heckman et al., 2016, 2018). Thus, the AMTE represents an empirically well-identified marginal benefit from adoption that an indifferent farmer considers before making an adoption transition decision.[11]

4.2 | Estimation of state transition probabilities

The state transition component of the farmer's conditional choice probability is estimated parametrically within the generalized ordered conditional probability framework. In particular, we estimate the discrete state transition probabilities as a continuation-ratio model, using a probit link function. The continuation-ratio model, unlike proportional odd models, specifies the conditional probability of a farmer being above a particular adoption state given that a farmer has attained that particular adoption state (Bauldry et al., 2018; Fullerton & Xu, 2016; Liu & Bai, 2019). The probability for any given value (w) of outcome (y) conditional on farmer's characteristics is

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the product of the probability that $y_j = w$ for the current adoption state j and the probability that $y_{j+1} > w$ for all earlier adoption states, which can be specified as follows:

$$Pr\left(y_{j+1}=w|x\right) = Pr\left(y_{j+1}=w|y_{j+1}\geq w,x\right) = \begin{cases} F\left\{\psi_1 - h(\boldsymbol{x})\right\} & w=1 \\ \left(\prod_{j=1}^{w-1}\left[1-F\left\{\psi_j - h(\boldsymbol{x})\right\}\right]\right) F\left\{\psi_w - h(x)\right\} & (1<w\leq W) \\ \prod_{j=1}^{W-1}\left[1-F\left\{\psi_j - h(\boldsymbol{x})\right\}\right] & w=W \end{cases}, \tag{20}$$

where Pr is the transition probability, y_{j+1} is the transition state with payoff categories ($w = 1,...,W$), $F(.)$ is a cumulative distribution function with probit link, $h(.)$ is a function of state variables $\boldsymbol{x}$, ψ_w is a vector of threshold indexes, and any other symbols remain as defined earlier.

5 | CONTEXT OF STUDY

Soil fertility constitutes a critical production input in agriculture and plays an important role in the welfare of poor subsistent agricultural societies (Kim & Bevis, 2019; Kleemann & Abdulai, 2013). With about 90% of the farming population in Ghana being subsistent and cultivating less than 2 ha of land (Ministry of Food and Agriculture, 2017), degradable soil conditions present a major challenge to food productivity and farm livelihoods, especially when 80% of Ghana's total agricultural output depends on this category of farmers (Ministry of Food and Agriculture, 2017). To maintain the productive capacity of soils in Ghana, scientific research organizations such as the International Institute of Tropical Agriculture (IITA) and the Council for Scientific and Industrial Research-Savannah Agricultural Research Institute (CSIR-SARI) and their partner organizations introduced the *Rhizobia* inoculant technology to smallholder grain legume farmers. One key crop that is targeted among other crops is soybean. The crop is targeted due to its potential to undergo sustainable intensification and the ability to provide large amounts of protein and other essential amino acids useful for consumption by humans and animals and for biofuel (Chibeba et al., 2018; Foyer et al., 2018; van Heerwaarden et al., 2018). The inoculant technology is an organic input containing isolates of an elite strain of a bacterial (*Bradyrhizobium* spp.) and an organic carrier material (Lupwayi et al., 2000). The inoculant technology is regarded as a cost-effective alternative to rehabilitating poor soils by enhancing the buildup of biological nitrogen fixation organisms in the soil (Giller, 2001).

The inoculant technology is expected to cost-effectively improve smallholder farmers' welfare by sustainably increasing productivity, while minimizing the cost of production, compared to inorganic inputs such as mineral fertilizers, which is sometimes priced out of reach for most smallholder farmers. The inoculant dissemination program was centered in the three regions (northern, upper east, and upper west) of northern Ghana, due to their soybean production potential in the country as well as the high incidence of extreme poverty in these parts of the country. The northern region, which is the focus of this study, is the second-poorest (30.7%) region in the country in terms of extreme poverty incidence followed by the upper-east region (27.7%), with the upper-west region (45.2%) ranking first in the country (Ghana Statistical

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Service, 2018). With soybean being a cash crop, it is expected that an increase in productivity will lead to an increase in the household income, which can contribute to poverty reduction for the poor households who depend on agriculture for income as well as food and nutrition security.

6 | SURVEY PROCEDURE AND DATA SOURCE

We use primary data from a recent survey of farm households in the northern region of Ghana, which was conducted from June to August 2018. The sample was drawn using a multi-stage sampling technique. The northern region was purposively selected because it is a major soybean growing hub in the country and also happens to be the largest beneficiary of the agricultural extension program that disseminated the novel inoculant technology. Cluster sampling technique was employed to zone the region into two clusters, consisting of the Eastern Corridor Zone (ECZ) and Western Corridor Zone (WCZ). Based on the districts' participation in the dissemination program and the intensity of soybean production in the districts within the clusters, eight districts, comprising four from each cluster, were purposively sampled. From the ECZ, Yendi, Saboba, Chereponi, and Karaga districts were selected, while in the WCZ, East Mamprusi, East Gonja, Savelugu, and Kumbungu districts were selected. In consultation with the field officers and agriculture extension agents in the selected districts, five to seven communities were proportionally sampled based on the dissemination channel received, program participation, and farmer population. Because the dissemination program was implemented through farmer-based organizations (FBOs), one FBO was randomly selected from a list of treated FBOs for each treated community and another randomly selected FBO from a list of untreated FBOs for each untreated community. Using a lottery approach, we randomly drew five farmers from each FBO. After a preliminary interview session with each of the selected farmers, using a computer-assisted personal interview (CAPI), a list of the farmers' information network members (INMs) in the community was compiled. The CAPI random number generator then used farmers' unique identification numbers to randomly sample three network members from each farmer's INMs for interview. A total of 600 farm households, comprising 325 participants and 275 nonparticipants, were interviewed in a face-to-face session.

We also collected detailed data on the farm household inoculant usage, capital assets, participation in nonfarm income generation activities, and livestock value, in addition to sociodemographic and farm characteristics. Table 1 presents the definition and descriptive statistics of the variables used in the analysis. A mean difference comparison in (Table A1 in the Appendix) reveals significant differences in socioeconomic characteristics between the dissemination program participants and nonparticipants. In particular, program participants significantly differ in gender, age, previous extension contacts, soil-quality conditions, and mode of inoculant acquisition compared to nonparticipants. Program participants also appear to have shorter distances to the nearest extension office and have amenities such as electricity and radio signals in their communities. However, it appears that program participants operate smaller farms, use less labor, experience lower level of rainfall, and live in smaller households compared to nonparticipants.

Using recall information from our cross-sectional survey, we constructed dynamic multistage adoption data, which is used for this analysis. In the absence of longitudinal data, farmers' recall information may be used to approximate the dynamic pattern of the adoption process

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TABLE 1 Descriptive statistics

Variables	Definition and measurement	Mean (*SD*)
Outcome variables		
Yield	Soybean yield per hectare (kg/ha)	829.64 (888.24)
Farm net returns	Gross revenue less variable cost (GHC/ha)	840.26 (762.11)
Decision variables		
Aware	Farmer is aware of inoculant = 1; otherwise = 0	0.84 (0.37)
Acknow	Farmer acquires knowledge on inoculant = 1; otherwise = 0	0.66 (0.47)
Tryout	Farmer's first use of inoculant = 1; otherwise = 0	0.32 (0.47)
Adopt	Farmer's second use of inoculant = 1; otherwise = 0	0.265 (0.44)
Cont-Adopt	Farmer's use inoculant at least for the third time = 1; otherwise = 0	0.26 (0.44)
Control variables		
Gender	Male = 1; female = 0	0.71 (0.46)
Age	Number of years	41.56 (13.32)
HHize	Number of people	5.78 (3.05)
Edu	Years of schooling	2.79 (4.69)
Farmsize	Number of hectares	5.05 (4.37)
Agrochem	Amount of active ingredient in gram used per hectare	4.00 (7.19)
Agrochemcost	Total cost of agrochemicals used per hectare (GHC)	57.67 (81.83)
Labor	Person's day worked per hectare	7.81 (24.23)
Laborcost	Total cost of person's day worked per hectare (GHC)	102.06 (155.36)
Extcont	At least one prior extension visit before inoculant = 1; otherwise = 0	0.54 (0.50)
Credit	Credit constraint = 0; otherwise = 1	0.83 (0.38)
District fixed effects		
WCZ	District is in the Western Corridor Zone = 1; Eastern Corridor Zone = 0	0.57 (0.50)
Measurement variables		
lnendwt	*Log* monetary value of household capital asset endowment in (GHC)	7.27 (1.79)
Asset_index	Household physical assets index	82.93 (122.59)
Nonfarminco	Farmer engaged in nonfarm work = 1; otherwise = 0	0.63 (0.48)
Livestock	Household livestock value (TLU)	1.18 (2.44)
Plot-level fixed effects		
Rainfall	Amount of rainfall (%)	61.63 (16.24)
Soil	Soil quality (scale 0–1)	0.623 (0.20)
Instruments		
Elradsig	Electricity and radio signal are in farmer's community = 1, otherwise = 0	0.95 (0.23)

(Continues)

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TABLE 1 (Continued)

Variables	Definition and measurement	Mean (*SD*)
Comextoff	Presence of extension agent in farmer's community = 1; otherwise = 0	0.63 (0.49)
Distexttof	Distance to nearest extension office/district capital (km)	18.86 (23.53)
Minac	Mode of inoculant acquisition: purchase = −1; gift = 1 and not available = 0	0.26 (0.67)
Unculand	Households have at least 1 ha of uncultivated land = 1; otherwise = 0	0.67 (0.47)
Commarkt	Presence of local market in farmer's community = 1; otherwise = 0	0.19 (0.39)
Observations (*N*)		600

Notes: The table shows the definition, measurement, and descriptive statistics of the farm households. With the inoculant technology being new to farmers, we employed a hybrid coding structure of Cooper et al. (2011) to give it direction for policy relevance. Therefore, farmers who acquire the technology without paying anything are coded as positive (+1), while those who purchased it are coded negative (−1) and no availability as zero (0). *SD*, standard deviation; WCZ, Western Corridor Zone.

(Besley & Case, 1993). We asked farmers the year they first heard of the inoculant technology and the year they first used the technology on their own farms. We also conducted an inoculant knowledge test and obtained farmers' inoculant knowledge test scores, a threshold of which we use to proxy for passive information acquisition (i.e., knowledge acquisition) in the adoption process. We gathered information on farmers' active participation in any field trial/demonstration on the use of the inoculant technology. Farmers who participated in field trials/demonstrations are deemed to have tried the technology[12] and therefore said to have acquired active information. Past studies that focused on adoption as a dynamic process failed to distinguish between the role played by active information acquisition and passive information acquisition. Intuitively, each of these modes of information acquisition may generate different learning outcomes and impacts on the adoption process (Feder & Slade, 1984). Exploiting farmers' repeated inoculant usage history and time differentials among farmers in our data, we constructed five ordered nodes of farmers' sequential adoption decisions[13] based on the synthetic cohort assumption (SCA).[14]

Table 2 presents the subsamples and characteristics of farmers at each cohort across the various stages of inoculant adoption. About 84% of farmers are at awareness stage; 66% at knowledge acquisition stage; 32% at trial stage; and 27% and 26% at adoption and continued adoption stages, respectively. Farmers at each cohort also appear to differ significantly in their observed characteristics.

Figure 1 shows the diffusion and adoption curves of the inoculant from 2014 to 2018, the self-reporting period covered in the survey. As observed in Figure 1, no farmer in our sample either heard or used the inoculant technology in 2014. It appears the dissemination program intensified in 2015 and peaked in 2016, when many farmers became aware of the technology. Within this period, adoption was slow until 2017, when most farmers began using the inoculant, an indication that diffusion of the inoculant technology may still be incomplete and farmers may be at different stages in the adoption process, justifying our argument to depart from the classical static adoption approach.

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TABLE 2 Comparison of farmer characteristics by adoption stages

	Aware	Acknow	Tryout	Adopt	Cont-Adopt
Variables	**Mean (SE)**	**Mean (SE)**	**Mean (SE)**	**Mean (SE)**	**Mean (SE)**
Yield	0.33*** (0.11)	0.04 (0.08)	0.17** (0.09)	0.30*** (0.09)	0.40*** (0.09)
Farm net return	0.12 (0.01)	−0.05 (0.08)	−0.14* (0.08)	−0.15* (0.08)	0.04 (0.08)
Gender (male = 1)	−0.03 (0.05)	0.10 (0.04)	0.06 (0.04)	0.06 (0.04)	−0.10** (0.04)
Age	2.33 (1.48)	3.05*** (1.14)	1.19 (1.17)	1.287 (1.23)	3.51*** (1.24)
HHSize	−0.38 (0.34)	−0.16 (0.26)	−0.46* (0.27)	−0.19 (0.28)	0.58**(0.28)
Edu	−0.01 (0.05)	0.03 (0.04)	0.05 (0.04)	0.08* (0.04)	−0.03 (0.05)
Farmsize	0.004 (0.49)	−0.42 (0.38)	−0.66* (0.38)	−0.61 (0.40)	0.04 (0.41)
Agrochem	0.07 (0.80)	−0.57 (0.62)	−0.75 (0.63)	−0.87 (0.66)	−0.16 (0.67)
Agrochemcost	−8.14 (9.11)	−5.33 (7.06)	−3.75 (7.20)	−7.49 (7.57)	−1.03 (7.65)
Labor	−1.81 (2.70)	−3.12 (2.09)	1.00 (2.13)	1.92 (2.24)	−0.88 (2.27)
Laborcost	−6.03 (17.31)	−22.72* (13.38)	8.79 (13.66)	12.34 (14.36)	−3.57 (14.53)
Extcont	0.62*** (0.05)	0.80*** (0.03)	0.18*** (0.04)	0.08* (0.05)	0.19*** (0.05)
Credit	−0.07 (0.04)	−0.08*** (0.03)	−0.02 (0.03)	−0.02 (0.04)	−0.04 (0.04)
Rainfall	−3.26* (1.81)	−2.45* (1.40)	0.40 (1.43)	0.52 (1.50)	−1.50 (1.52)
Soil	0.02 (0.02)	0.02 (0.02)	0.03 (0.02)	0.03 (0.02)	0.01 (0.02)
WCZ	−0.09* (0.06)	−0.02 (0.04)	0.06 (0.04)	0.04 (0.05)	0.03 (0.05)
Comextoff	−0.12** (0.05)	−0.02 (0.04)	0.06 (0.04)	0.06 (0.05)	−0.002 (0.05)
Distextoff	−6.46** (2.79)	−4.38** (2.16)	−6.82*** (2.19)	−8.16*** (2.30)	−5.24** (2.34)
Elradsig	−0.02 (0.03)	0.01 (0.00)	−0.01 (0.02)	−0.01 (0.02)	0.004 (0.02)
Commarkt	−0.01 (0.04)	−0.02 (0.03)	−0.08*** (0.03)	−0.08** (0.04)	0.05 (0.04)
Minac	0.31*** (0.07)	0.14*** (0.06)	0.46*** (0.06)	0.58*** (0.06)	−0.32*** (0.06)
Unculand	−0.07 (0.05)	−0.04 (0.04)	−0.08* (0.04)	−0.08* (0.04)	−0.06 (0.04)
Asset_index	15.46 (13.65)	−2.87 (10.59)	6.14 (10.78)	4.89 (11.35)	7.46 (11.46)

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TABLE 2 (Continued)

Variables	Aware	Acknow	Tryout	Adopt	Cont-Adopt
	Mean (SE)	**Mean (SE)**	**Mean (SE)**	**Mean (SE)**	**Mean (SE)**
Nonfarminco	–0.03 (0.05)	0.01 (0.04)	0.03 (0.04)	0.07 (0.05)	0.04 (0.05)
Livestock	0.18 (0.27)	0.19 (0.21)	0.11 (0.21)	0.06 (0.23)	0.14 (0.23)
Endwt	318.74 (1,425.30)	369.43 (1,104.36)	89.70 (1,124.92)	196.64 (1,183.99)	2,145.04 (1,193.10)
Subsamples	504	397	189	159	154

Notes: ***, **, and * are 1%, 5%, and 10% significance levels, respectively; values in brackets are standard errors (SE). The table shows the differences in mean comparison of farmers at various binary decision nodes (e.g., aware vs. unaware, acquire knowledge vs. no-knowledge, tryout vs. no-tryout, adopt vs. nonadopt, continued adoption vs. discontinued adoption). WCZ, Western Corridor Zone.

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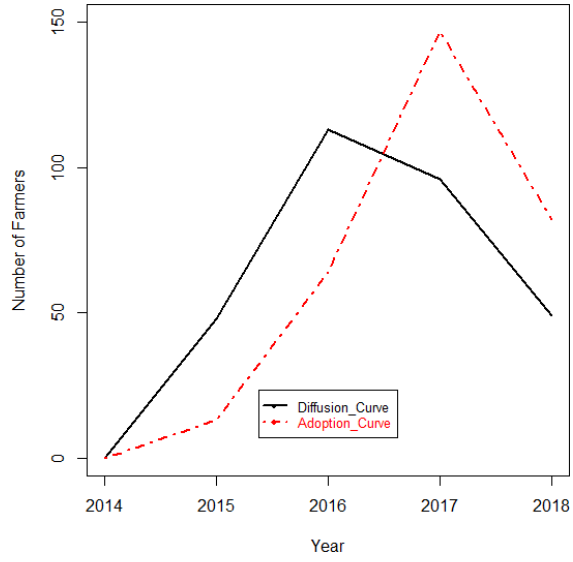

FIGURE 1 Inoculant technology diffusion and adoption in northern region, 2014–2018 [Colour figure can be viewed at wileyonlinelibrary.com]

7 | EMPIRICAL RESULTS

7.1 | Determinants of adoption transition decisions

Table 3 presents the results on factors that determine farmers' decision to transit from one adoption state to the other, as expressed in Equation 20 of the empirical specifications. The table contains the estimates of two different specifications of the equation (models 1 and 2). Model 1 assumed homogeneity in farmers' characteristics as well as benefits across adoption states (i.e., it implies the parallel line/proportional-odd assumption). That is, model 1 constraints coefficients across all transitions to be equal. Model 2 relaxes the parallel line assumption to account for heterogeneity that exists among farmers and the benefits accruing to farmers at different adoption states. The specification in model 2 is important because when a farmer makes sequential adoption decisions, but are misspecified as a single dichotomous decision, that can lead to serious statistical bias and inconsistent estimates (Buis, 2017; Williams, 2016). A log-likelihood ratio test (reported in the last row of Table 3) between the two models shows that model 2 is a better fit of the farmers' adoption decision-making problem, compared to model 1. Therefore, we restrict the discussion in this section to the estimates of model 2.

First, we discuss the threshold-crossing indexes describing the adoption transition behavior of farmers, reported in the last row of Table 3. The table shows that all the threshold indexes across the two models are positive. In particular, the estimates in model 1 are significantly different from zero (at 5% and 1% levels, respectively) across all the adoption states, suggesting that farmer characteristics as well as adoption states are heterogeneous, contrary to the model's assumption. Compared to model 2, the threshold estimates of model 1 are generally downward biased, indicating that farmers make sequential adoption decisions, which if ignored could underestimate farmers' adoption behavior. In particular, the threshold index reveals that farmers at knowledge acquisition state expect 1.3% probability of yield increment to move to trial state and 2% yield increment for farmers at trial state to move to adoption state. Interestingly, farmers who moved into

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TABLE 3 Determinants of adoption states transition decision

	All states	Acknow	Tryout	Adopt	Cont-Adopt
	Model 1	Model 2	Model 2	Model 2	Model 2
Variables	Coefficients (SE)	Coefficients (SE)	Coefficients (SE)	Coefficients (SE)	Coefficients (SE)
Gender (male = 1)	−0.14 (0.10)	−0.37 (0.23)	−0.16 (0.17)	0.08 (0.18)	−0.60** (0.22)
Age	0.04** (0.02)	0.09** (0.04)	0.06** (0.03)	0.03 (0.03)	−0.05 (0.04)
Age^2	−3-e4* (2-e4)	−0.001 (0.001)	−0.001** (3-e4)	−3-e4 (3-e4)	0.001 (0.001)
HHSize	0.01 (0.01)	−0.01 (0.03)	0.03 (0.02)	0.002 (0.03)	−0.05 (0.05)
Edu	0.11 (0.09)	0.39* (0.2)	0.30* (0.17)	−0.04 (0.17)	−0.53** (0.28)
Farmsize	−0.01 (0.02)	−0.02 (0.04)	−0.03 (0.03)	−0.02 (0.04)	0.03 (0.05)
Agrochem	0.002 (0.01)	0.01 (0.02)	0.01 (0.03)	0.003 (0.03)	−0.09 (0.06)
Agrochemcost	−0.001 (0.001)	−0.001 (0.001)	−0.003 (0.003)	7-e6 (0.003)	0.004 (0.01)
Labor	0.01 (0.01)	0.02** (0.01)	0.01 (0.01)	0.01 (0.01)	−0.002 (0.01)
Laborcost	−0.001 (0.001)	−0.003* (0.001)	−0.001 (0.001)	−0.001 (0.001)	0.002 (0.002)
Extcont	0.98*** (0.09)	2.53*** (0.29)	0.54*** (0.15)	0.94*** (0.17)	1.35*** (0.38)
Credit	−0.078 (0.097)	−0.191 (0.324)	−0.001 (0.177)	−0.106 (0.183)	−0.107 (0.253)
Rainfall	0.001 (0.002)	−0.004 (0.01)	0.01 (0.004)	0.002 (0.01)	−0.01* (0.01)
Soil	0.44** (0.20)	0.78* (0.45)	0.19 (0.37)	0.24 (0.30)	0.17 (0.64)
WCZ	0.19** (0.08)	0.42** (0.22)	0.09 (0.15)	0.04 (0.16)	0.67*** (0.23)
Distextof	−0.01*** (0.002)	−0.01 (0.003)	−0.01*** (0.003)	0.01 (0.004)	−0.01 (0.01)
Comextoff	0.08 (0.08)	0.08 (0.20)	0.11 (0.14)	0.03 (0.16)	−0.32 (0.25)
Elradsig	0.07 (0.14)	−0.35 (0.35)	0.23 (0.28)	0.01 (0.33)	5.93*** (0.62)
Minac	0.11* (0.06)	0.66*** (0.13)	0.42*** (0.08)	−0.07 (0.08)	−0.50*** (0.12)
Unculand	−0.23*** (0.09)	−0.25 (0.21)	−0.17 (0.14)	−0.22 (0.15)	0.10 (0.22)
Commarkt	0.05 (0.10)	0.23 (0.25)	0.25 (0.18)	−0.23 (0.19)	0.24 (0.30)

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TABLE 3 (Continued)

	All states	Acknow	Tryout	Adopt	Cont-Adopt
	Model 1	Model 2	Model 2	Model 2	Model 2
Variables	Coefficients (SE)	Coefficients (SE)	Coefficients (SE)	Coefficients (SE)	Coefficients (SE)
Model−1 (Thre-index (I))		0.33 (0.48)	1.05** (0.48)	1.59*** (0.49)	2.64*** (0.50)
Model−2 (Thre-index (I))		1.34 (1.21)	1.68** (0.83)	1.38 (0.97)	5.35*** (1.35)
Transition probability		0.90 [0.19]	0.67 [0.16]	0.92 [0.14]	0.77 [0.31]
LL	−733.40	−651.46			
Wald χ^2	182.31***	676.60***			
LR test χ^2 (2)	163.87***				
Observations (N)	536	536			

Notes: ***, **, and * are 1%, 5%, and 10% significance levels, respectively; values in parentheses are robust standard errors, while values in brackets are standard deviations. The table shows the estimates from the generalized continuation-ratio probit model as represented by Equation 6 in the empirical specification, which measures the conditional probability $\left[Pr\left(\boldsymbol{I_j} < \boldsymbol{I_{j+1}} | \boldsymbol{X} = x, \boldsymbol{Z} = z, \boldsymbol{\theta} = \overline{\theta}, Q_j = 1\right)\right]$ of a farmer moving from adoption state j to $j + 1$. LL, Log-likelihood; LR, Likelihood Ratio; and WCZ, Western Corridor Zone.

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adoption state expect 5% yield increment to continue their adoption, suggesting that after trial and adoption of a new technology, high-benefit expectations could be a driving factor for farmers' continued adoption of the technology. This finding is in line with Lambrecht et al. (2014), who made similar observations in their study of mineral fertilizer adoption in eastern Congo that higher expectations of potential returns from adoption by farmers after trials have negative influence on continued adoption. Intuitively, this means that farmers' perception of gaining an additional unit benefit is very high in arriving at a final adoption decision. In addition, the threshold index is monotonic across adoption states, indicating heterogeneity in state-specific marginal benefits as well as sorting in the adoption behavior of farmers (Buis, 2017; Lindeboom & van Doorslaer, 2004). To the extent that agents sort on gains, this implies that farmers' adoption decisions are sequential, as captured in our dynamic specification, rather than dichotomous, as often assumed in classical adoption models (see Buis, 2017; Mare, 2006, 2011).

Table 3, last row, also reports the average transition probabilities at each adoption state. The transition probability measures the chances that a farmer who attains a particular adoption state passes on to the next higher adoption state. The intuition is that farmers at higher adoption states obtain higher benefits compared to farmers at lower states (Buis, 2017). The results show that, on average, 90% of farmers at awareness state pass through to knowledge acquisition state and 67% of farmers at knowledge acquisition state pass through to the trial state, underscoring the importance of extension information provision and promotion campaigns in the diffusion and adoption process of new agricultural technologies (Anderson & Feder, 2007; Takahashi et al., 2020). The table further reveals that 92% of trial farmers pass to adoption state and 77% of the farmers at adoption state pass to continued adoption state, suggesting that more farmers are likely to demand the inoculant technology after two rounds of usage due to higher benefits. In addition, because benefits differ between farmers who attain a particular adoption state and those who did not, it means that, at each stage, farmers can learn more about average benefits of the new technology from other farmers. Therefore, the probability of more farmers adopting the new technology increases due to learning, as information acquisition and adoption decisions of new agricultural technologies are often jointly determined (Abdulai et al., 2008).

In lieu of the fact that determinants of adoption have been extensively discussed in the conventional technology adoption literature, we focus the present discussion on the determinants of farmers' transition decisions along the adoption chain. Understanding these factors will be helpful in revealing farmers' technology adoption behavior and can contribute to the design and implementation of targeted extension dissemination policies to maximize resources. However, the estimates for the discrete adoption choice decisions (i.e., Equations 8 and 9) are presented in Appendixes A1 and A2. The individual predictors in model 2 are discussed as factors influencing farmers' decisions to transit from one adoption state to another. A positive coefficient of a predictor is interpreted as the conditional probability of being at a particular adoption state and moving beyond to the next higher state where margins of benefits are perceived to be greater, while the reverse is true for a negative coefficient (Bauldry et al., 2018; Liu & Bai, 2019).

Table 3 shows that the coefficient of extension contact (*Extcont*) is positive and statistically significant in all adoption states, suggesting that extension is central to the transition decisions of farmers at all phases of adoption. The implication is that continued extension support to farmers is required right from awareness creation and technical knowledgeable supply until farmers adopt and continue to use the technology, a finding that is consistent with the argument that knowledge-intensive agricultural technologies require skilled extension staff to facilitate the adoption process (Issahaku & Abdulai, 2019; Takahashi et al., 2020).

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Table 3 further reveals that the mode of technology acquisition (*Minac*) plays an important role in farmers' adoption transition decisions. The results reveal that farmers who acquire the inoculant free are more likely to move from awareness state to trial state but are less likely to get to adoption and continued adoption states. This implies that free distribution of new divisible technologies to farmers during dissemination programs has high probability in creating awareness, getting farmers to acquire knowledge, and trying the technology but may not lead to adoption and continued adoption. Conversely, farmers whose mode of acquisition is by purchase have high probability of getting to continued adoption, compared to farmers who had free supply or no access to the technology. This indicates that input markets to ensure constant supply of the new technology to farmers may be indispensable in getting farmers into adoption and continued adoption states of the technology. This finding agrees with Shiferaw et al. (2015), who found input supply constraints to be responsible for nonadoption of improved groundnut variety among adoption-willing farmers in Uganda.

Table 3 also shows that farmers' location (WCZ) has a positive effect on their adoption transition decisions, suggesting that farmers located in close proximity to the source of supply of the technology are more likely to move beyond knowledge acquisition state to adoption and continued adoption states compared to farmers living far from the source. In particular, farmers living closer to the nearest extension office (*Distextof*) are more likely to move beyond trial and adoption states to continued adoption state, suggesting that access to better infrastructure, such as information and good road networks, positively influences farmers' adoption transition decisions, a finding that is in line with Suri's (2011) suggestion that removing supply and infrastructure constraints may be a cost-effective method to facilitate the adoption of improved agricultural technologies among farmers.

Table 3 also shows that soil quality (significant at the 1% level) plays an important role in farmers' adoption transition decisions, especially when the technology has positive long-term effects on maintaining the productive capacity of the soil. The results reveal that farmers who perceived the quality of soil in their farm plots to be fertile or good are more likely to move beyond the inoculant knowledge acquisition state to adoption and continued adoption states.[15] However, the coefficient of rainfall at the continued adoption state is negative (significant at the 10% level), indicating that inadequate rainfall may negatively influence farmers' continued adoption decision. This finding is similar to that of Shahzad and Abdulai (2021), who found the average daily rainfall to have a negative influence on farmers' adoption decisions of climate-smart farm practices in Pakistan.

Furthermore, Table 3 shows that the coefficient of age is positive and statistically significant in all adoption states (except at the continued adoption state), while the squared term has a negative and statistically significant coefficient across all adoption states but positive at the continued adoption state. This finding suggests that at younger ages, an increase in age increases the probability of adoption, with the maximum effect occurring at approximately 46 years, while at older ages, the probability of adoption decreases with increasing age. However, once adoption occurs, older farmers who are more experienced are likely to benefit from the new technology more than younger farmers and are therefore more likely to remain in continued adoption. This finding corroborates Lambrecht et al. (2014), who found older and more experienced farmers to be more efficient and better judges of expected returns than less-experienced younger farmers, resulting in higher continued adoption rates of mineral fertilizer among older farmers in eastern Congo.

Table 3 also shows that education is positive in the transition decision of farmers from awareness to knowledge acquisition and trial states (significant at the 10% level, respectively) but negative at adoption and continued adoption states (significant at the 1% level), suggesting that

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increasing levels of education increase the probability of learning about the new technology at the early stages in the technology adoption or diffusion process and decrease at later stages after farmers have learnt more about the new technology.

7.2 | Impact on returns to inoculant adoption

In this section, we present the results on the impact of inoculant adoption on yields and farm net returns in Tables 4 and 5, respectively. The results are obtained from the estimates of Equation 15 and computed using Equation 16. The estimated impacts represent the observed case that the farmer makes a transition to a particular adoption stage and the counterfactual case that the farmer did not make the transition. Therefore, the results are the direct average effects on yields and farm net returns at each adoption state that the farmer attained.[16] For brevity, we focus the discussion on the yields (Table 4) and extend it to the farm net returns (Table 5). Both Tables 4 and 5 show a positive and statistically significant impact of inoculant adoption on yields and farm net returns, respectively, across all adoption states. The results in Table 4 reveal that, on average, the yield for farmers who used the inoculant for the first season (i.e., at the trial state) was 108 kg/ha of soybeans, with the yields increasing to 151 and 191 kg/ha for farmers who used it for at least two seasons (i.e., at the adoption state) and farmers who used it for at least three seasons (i.e., at the continued adoption state), respectively. We observe a pattern of marginal incremental benefits as farmers move from one adoption state to the other, suggesting that farmers may still be learning about the inoculant technology, and the benefits are heterogeneous, depending on the adoption state of the farmer. This finding is consistent with van Heerwaarden et al. (2018), who found the average yields to be in the range of 102–180 kg/ha in an on-farm experimental trial of the inoculant across 10 countries in SSA. On the contrary, the average farm net returns for farmers are 56 GHC/ha at the trial state, 51 GHC/ha at the adoption state, and 49 GHC/ha at the continued adoption state (see Table 5), suggesting that early adopters of the inoculant benefit more in terms of revenue due to marginal increases in their yields in those seasons. This observation is consistent with the literature on diffusion and adoption of new technologies, where early

TABLE 4 Impact on yield (kg/ha)

Treatment effects	Acknow (1)	Tryout (2)	Adopt (3)	Cont-Adopt (4)
ATE†	0.66*** (0.29)	0.94*** (0.03)	1.35*** (0.04)	1.73*** (0.07)
ATE	0.73*** (0.03)	1.08*** (0.03)	1.51*** (0.05)	1.91*** (0.08)
ATT	0.75*** (0.03)	1.06*** (0.04)	1.45*** (0.06)	2.08*** (0.11)
ATUT	0.34*** (0.13)	1.11*** (0.06)	2.06*** (0.13)	1.70*** (0.13)
AMTE†	1.58*** (0.07)	1.60*** (0.08)	1.57*** (0.08)	1.69*** (0.09)
AMTE	1.96*** (0.07)	1.87*** (0.09)	1.77*** (0.10)	2.09*** (0.13)

Notes: ***, **, and * are 1%, 5%, and 10% significance levels, respectively; values in brackets are standard errors. The table shows the estimates of the treatment effects (without continuation values) of the adoption process on soybean net returns. ATE is the average treatment effects for farmers at each adoption state; ATE† is the average treatment effects for the full population of farmers; ATT is the average treatment effects for farmers who chose to transit to a higher adoption state; ATUT is the average treatment effects for farmers who chose not to transit to a higher adoption state. The average marginal treatment effect (AMTE) is the average effects for farmers at an adoption transition state who are indifferent between transiting and not transiting to a higher-level adoption state. AMTE† is the average marginal effects for the full population of farmers who are indifferent between transiting and not transiting to a higher-level adoption state.

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TABLE 5 Impact on farm net returns (GHC/ha)

Treatment effects	Acknow (1)	Tryout (2)	Adopt (3)	Cont-Adopt (4)
ATE†	0.43*** (0.03)	0.46*** (0.03)	0.48*** (0.04)	0.51*** (0.05)
ATE	0.50*** (0.02)	0.56*** (0.03)	0.51*** (0.04)	0.49*** (0.04)
ATT	0.54*** (0.02)	0.51*** (0.03)	0.47*** (0.04)	0.62*** (0.06)
ATUT	0.02 (0.05)	0.67*** (0.04)	0.85*** (0.13)	0.34*** (0.06)
AMTE†	0.48*** (0.05)	0.49*** (0.06)	0.49*** (0.06)	0.58*** (0.07)
AMTE	0.60*** (0.04)	0.50*** (0.05)	0.45*** (0.05)	0.67*** (0.07)

Notes: ***, **, and * are 1%, 5%, and 10% significance levels, respectively; values in brackets are standard errors. The table shows the estimates of the treatment effects (without continuation values) of the adoption process on soybean net returns. ATE is the average treatment effects for farmers at each adoption state; ATE† is the average treatment effects for the full population of farmers; ATT is the average treatment effects for farmers who chose to transit to a higher adoption state; ATUT is the average treatment effects for farmers who chose not to transit to a higher adoption state. The average marginal treatment effect (AMTE) is the average effects for farmers at an adoption transition state who are indifferent between transiting and not transiting to a higher-level adoption state. AMTE† is the average marginal effects for the full population of farmers who are indifferent between transiting and not transiting to a higher-level adoption state.

adopters tend to get the greatest returns, thereby triggering the race to high-order adoption (e.g., Karshenas & Stoneman, 1993).

Table 4 further shows that the AMTE for farmers at various margins of indifference deciding whether to make the next transition or remain where they are, in terms of yields, is 187 kg/ha for farmers at the trial state, 177 kg/ha at the adoption state, and 209 kg/ha at the continued adoption state. The AMTE for farm net returns (Table 5) is 50 GHC/ha for farmers at the trial state, 45 GHC at the adoption state, and 67 GHC/ha at the continued adoption state. The AMTE estimates for both outcome measures are positive across all adoption states and significant at the 1% level, suggesting that farmers with unobserved factors (e.g., wealth endowment) that increase their ability to make further adoption investment decisions stand to gain more from such investment decisions. In other words, farmers who tried the inoculant technology and have the financial ability to continue to use the inoculant benefit more from their continued adoption. We also observe from the results in Tables 4 and 5 that the impact gap is wider for yields, compared to that of farm net returns, which can be attributed to differences in prices faced by farmers (both input and output prices), timing, and place of sales.

Figures 2 and 3 present the distributions of impacts at the subpopulation level of farmers at each adoption state. We find that farmers who are observed to make a transition at each adoption state (i.e., the treated case—TT) obtain higher yields and farm net returns compared to if the same farmers did not make the transition (i.e., the untreated case—TUT). The results reveal that the impact distributions at the subpopulation means for both outcomes are positive and above the subpopulation means at zero. Examining the pattern of the impact distributions at the subpopulation means reveals an interesting finding. In particular, we observe a positive pattern of selection on gains (i.e., TT > ATE > TUT) at the knowledge and continued adoption states and a negative or reverse pattern of selection (i.e., TUT > ATE > TT) at the trial and adoption states.[17] The negative selection on gains at the trial and adoption states suggests that farmers who would have benefited from further investment in the new technology are unable to transit to the continued adoption state due to low levels of unobserved factors (i.e., wealth endowment). Intuitively, the implication is that further investment in the inoculant dissemination program activities that provide subsidized access to the inoculant technology for this category of farmers has a high potential of increasing their productivity as well as moving them into the continued adoption state.

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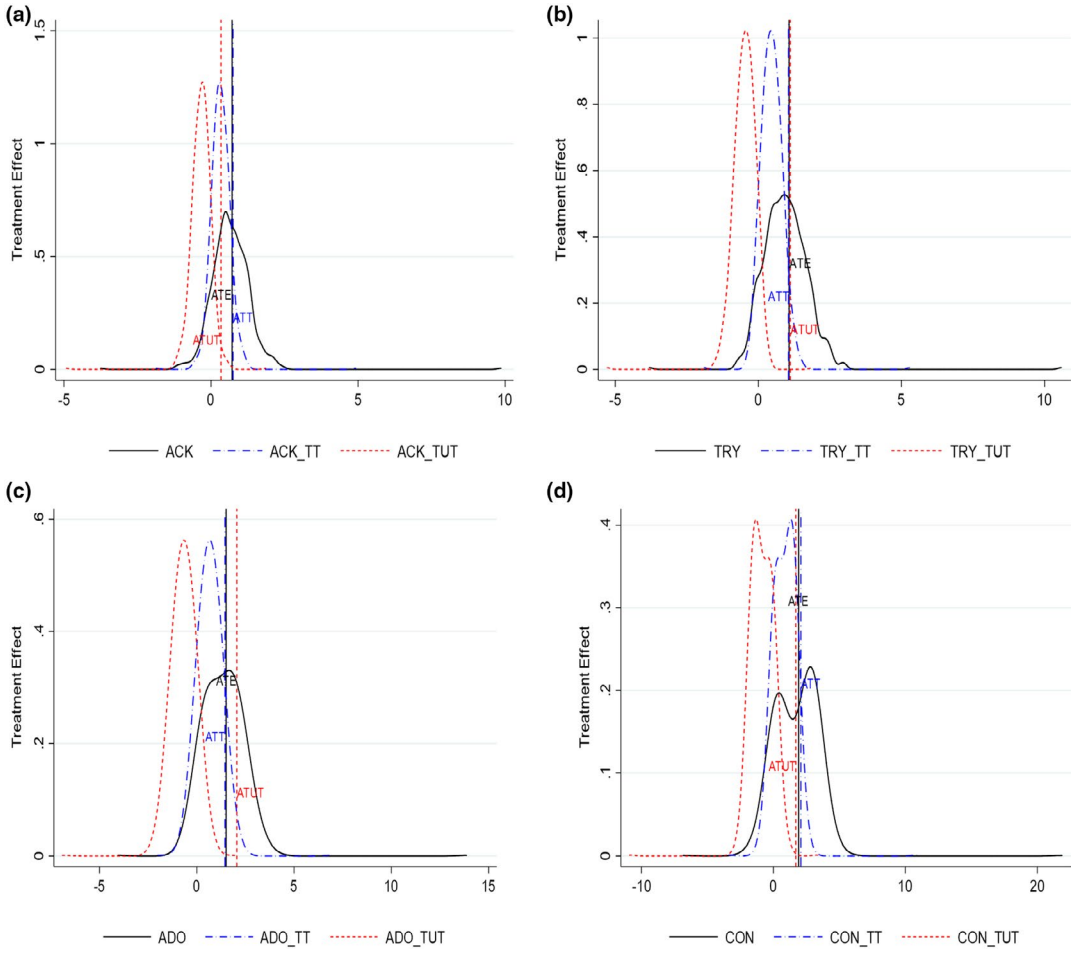

FIGURE 2 Treatment effect distributions at each adoption transition (subpopulation level) – yield (kg/ha). ACK, knowledge acquisition state; TRY, trial state; ADO, adoption state; CON, continued adoption state; TT, treated state; TUT, untreated state. ATE, average treatment effect curve; ATT, average treatment effect on the treated curve; ATUT, average treatment effect on the untreated curve [Colour figure can be viewed at wileyonlinelibrary.com]

Conversely, the positive selection on gains suggests that the category of farmers who transition into the continued adoption state due to high wealth endowment attained high benefits from the technology. However, the extent of the benefits would have been much higher for the category of farmers who are unable to transit into the continued adoption state, suggesting that the inoculant technology may be more beneficial to poor farmers compared to wealthy farmers.

7.3 | Long-term impact of returns to inoculant adoption

In this section, we present the results derived from the estimates of Equation 17 in the empirical specification in Tables 6 and 7 for yields and farm net returns, respectively. The results represent the long-term impact of technology adoption, which approximates ex post valuation of opportunities that farmers' current adoption decisions open up for them. As noted by Besley and

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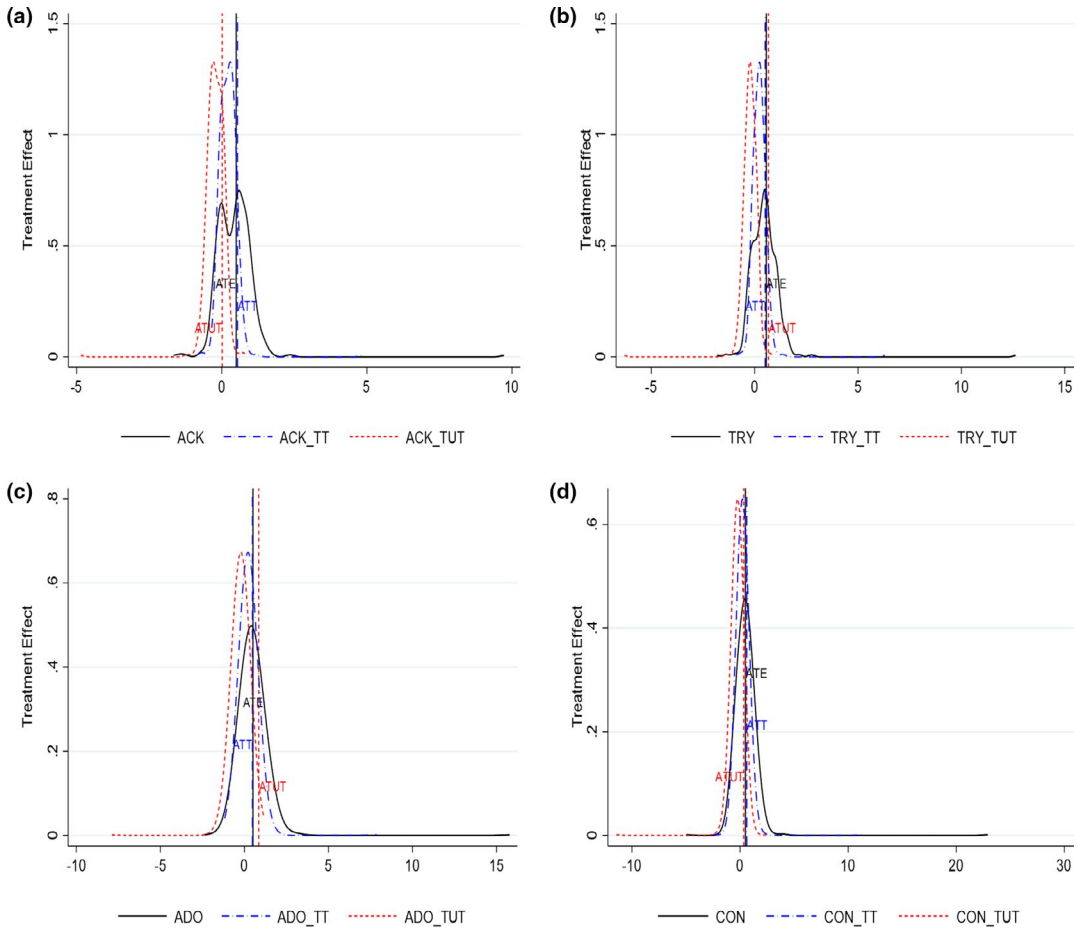

FIGURE 3 Treatment effect distributions at each adoption transition (subpopulation level) – net returns (GHC/ha). ACK, knowledge acquisition state; TRY, trial state; ADO, adoption state; CON, continued adoption state; TT, treated state; TUT, untreated state. ATE, average treatment effect curve; ATT, average treatment effect on the treated curve; ATUT, average treatment effect on the untreated curve [Colour figure can be viewed at wileyonlinelibrary.com]

Case (1993), current adoption choices have future consequences and have to be considered when analyzing farmers' adoption choices. Intuitively, farmers who try a technology are more likely to adopt, and those who adopt conditional on the benefits are more likely to sustain their adoption. This valuation of the dynamic impact of opportunities constitutes the long-term forecast of benefits informing farmers' adoption decisions but is often overlooked in traditional technology adoption impact studies.

The results in Tables 6 and 7 show similar patterns in the distribution of benefits, similar to those computed without the inclusion of the continuation values presented in Tables 4 and 5. All the estimated coefficients are positive and statistically significant at the 1% level, indicating that farmers' valuation of expected long-term benefits at each adoption state is important in the adoption decisions they make. The estimates of ATE presented in row 2 of Table 6 suggest that the average total effect on yields for farmers at the trial state is 204 kg/ha. Similarly, the effects for farmers at the adoption and continued adoption states are 298 and 329 kg/ha, respectively. In terms of farm net returns, presented in Table 7, we find the average total effect to be

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TABLE 6 Impact on yield estimates with continuation values (kg/ha)

Treatment effects	Acknow (1)	Tryout (2)	Adopt (3)	Cont-Adopt (4)
ATE†	1.09*** (0.04)	1.76*** (0.07)	2.55*** (0.10)	2.93*** (0.13)
ATE	1.14*** (0.04)	2.04*** (0.06)	2.98*** (0.11)	3.29*** (0.14)
ATT	1.17*** (0.04)	2.02*** (0.07)	2.83*** (0.11)	3.57*** (0.19)
ATUT	0.78*** (0.19)	2.09*** (0.10)	4.33*** (0.20)	2.95*** (0.13)
AMTE†	6.64*** (0.40)	7.65*** (0.36)	7.68*** (0.39)	7.55*** (0.40)
AMTE	8.19*** (0.35)	9.01*** (0.36)	8.61*** (0.39)	8.80*** (0.64)

Notes: ***, **, and * are 1%, 5%, and 10% significance levels, respectively; values in brackets are standard errors. The table shows the estimates of the total dynamic treatment effects (including continuation values) of the adoption process on soybean yields. ATE is the average treatment effects for farmers at each adoption state; ATE† is the average treatment effects for the full population of farmers; ATT is the average treatment effects for farmers who chose to transit to a higher adoption state; ATUT is the average treatment effects for farmers who chose not to transit to a higher adoption state. The average marginal treatment effect (AMTE) is the average effects for farmers at an adoption transition state who are indifferent between transiting and not transiting to a higher-level adoption state. AMTE† is the average marginal effects for the full population of farmers who are indifferent between transiting and not transiting to a higher-level adoption state.

TABLE 7 Impact on farm net returns estimates with continuation values (GHC/ha)

Treatment effects	Acknow (1)	Tryout (2)	Adopt (3)	Cont-Adopt (4)
ATE†	0.66*** (0.05)	0.71*** (0.06)	0.76*** (0.08)	0.79*** (0.10)
ATE	0.77*** (0.04)	0.91*** (0.04)	0.85*** (0.07)	0.78*** (0.08)
ATT	0.86*** (0.04)	0.82*** (0.05)	0.76*** (0.07)	0.99*** (0.01)
ATUT	–0.14 (0.19)	1.09*** (0.07)	1.67*** (0.21)	0.52*** (0.11)
AMTE†	2.70*** (0.32)	2.71*** (0.35)	2.66*** (0.35)	3.16*** (0.40)
AMTE	3.56*** (0.22)	2.98*** (0.27)	2.59*** (0.27)	3.95*** (0.39)

Notes: ***, **, and * are 1%, 5%, and 10% significance levels, respectively; values in brackets are standard errors. The table shows the estimates of the total dynamic treatment effects (including continuation values) of the adoption process on soybean net returns. ATE is the average treatment effects for farmers at each adoption state; ATE† is the average treatment effects for the full population of farmers; ATT is the average treatment effects for farmers who chose to transit to a higher adoption state; ATUT is the average treatment effects for farmers who chose not to transit to a higher adoption state. The average marginal treatment effect (AMTE) is the average effects for farmers at an adoption transition state who are indifferent between transiting and not transiting to a higher-level adoption state. AMTE† is the average marginal effects for the full population of farmers who are indifferent between transiting and not transiting to a higher-level adoption state.

91 GHC/ha for farmers at the trial state, 85 GH/ha at the adoption state, and 78 GHC/ha at the continued adoption state. Tables 6 and 7 also show that the total AMTE estimates at all adoption states are positive and statistically significant at the 1% level. In particular, the results reveal that the total AMTE for farmers at the margin of trial is 901 kg/ha, for farmers at the margins of adoption is 861 kg/ha, and for farmers at the margins of continued adoption is 880 kg/ha. These estimates are close to the experimental results of van Heerwaarden et al. (2018), who found the average total yield of 1,343 kg/ha obtained by inoculant users in an on-farm experiment in 10 countries of SSA. A plot of the full distributions of the total treatment effects at both population and subpopulation levels reveals similar distributions of impacts[18] and selection on gains pattern among the farmers. The implication of this finding is that there exist potential long-term benefits from the adoption of inoculant technology as farmers' yields and farm net returns appear to more than double, compared to the short-term benefits. This observation resonates with

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the benefit stream of organic agricultural inputs that have long-term impacts on improving soil fertility.[19]

7.4 | Robustness check

The validity of our treatment effects depends on proper identification of the unobserved wealth endowment effect on farmers' transitional ability, as expressed in the factor model in Equation 12 of the empirical specification. In the interest of brevity, we discuss the distributions of the unobserved factors as well as the heterogeneity of the factors across each adoption state but present the results in the appendix, by way of robustness check. Figure A6 presents the combination of two normal distributions of the unobserved wealth endowment for farmers at each adoption state (see Appendix A8). The results show evidence of sorting into adoption states by unobserved wealth endowment, with this endowment having significant impact on the distributions of farm outcomes. The distributions around the zero mean confirm our findings of the existence of two heterogeneous groups of farmers based on selection on gains, that is, the negative and positive selection on gains groups of farmers.

Figure A7 in Appendix A9 presents the distributions of the unobserved wealth endowments for farmers at each adoption state. We observe that the distributions of the endowment are heterogeneous across each adoption state, indicating that farmers' wealth endowment may play an important role in moving them from one adoption state to the next adoption state.

Finally, Table A3 presents the results of exogeneity test for the instrumental variables (IVs) employed as exclusion restriction variables for the identification of farmers' adoption choice decisions at each adoption state as expressed in Equation 12 of the empirical specifications. In line with Heckman et al. (2018), we employed state-dependent IVs to identify each autonomous adoption decision, while controlling for farmer's wealth endowment at each adoption state. We assume that different adoption states are identified by different instruments that are important to that state. As observed in Table A3, the Anderson–Rubin test statistic of the IVs in both the yields and the farm net returns models is not statistically significant at any conventional level, indicating that the IVs' use for the exclusion restriction satisfies the exogeneity requirements and that the instruments do not have direct influence on yields and farm net returns, except through the different states of adoption that they identify.[20]

8 | CONCLUSIONS AND IMPLICATIONS

In this study, we address the question of what drives the dynamic pattern of farmers' technology adoption decisions over time. Using farm-level data of soybean farmers in Ghana, we analyzed technology adoption as a multi-stage dynamic decision problem and how adoption influences farm outcomes such as yields and net returns. We employed the dynamic treatment effect model, a novel procedure, to examine heterogeneity in returns to adoption of newly introduced technologies, focusing on the newly introduced inoculant technology. Our findings reveal new insights into the role of information in farmers' adoption decisions, the distribution of returns in the entire chain of the adoption process, and factors that influence continued adoption, or otherwise, of new agricultural technologies. Consistent with Besley and Case (1993), we find substantial impact heterogeneity at each adoption state, which, we contend, drives the adoption process.

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Our empirical results suggest that farmers have high-benefit expectation stream for newly introduced agricultural technologies and exhibit sorting behavior in their adoption decisions. As a result, farmers may discontinue their adoption if the returns are below their expectations at any point in time due to disappointment. It is therefore important that technology dissemination programs employ different strategies that maximize farmers' returns at each stage in the adoption process to sustain farmers' adoption inertia. Moreover, expectation management should be built into new technology dissemination and promotion campaigns to minimize farmers' disappointments.

The findings also suggest that although the free distribution of newly developed divisible agricultural technologies to farmers during dissemination programs increases farmer technology awareness, knowledge acquisition, trial, and implementation, it does not guarantee continued adoption as argued by Lambrecht et al. (2014). In contrast, the results indicate that the existence of efficient input markets and continued information supply tends to drive the probability of continued adoption. Therefore, extension programs aimed at promoting new agricultural technologies should provide information on market outlets for accessing the technology to ensure continued adoption. The results further revealed that the long-term benefits of the inoculant technology are higher than the short-term benefits, conditional on the markets being able to absorb the excess supply that may result from higher yields. In addition, the findings suggest that subsidizing the inoculant technology to poor farmers will have an enormous impact on poverty reduction, through farmers' yields and farm net returns improvement.

Furthermore, the study revealed that continued extension support to farmers at all phases in the adoption process, provision of rural infrastructure such as information and communication, and good road networks contribute significantly to maintaining farmers' adoption inertia. The findings also reveal that education plays a significant role at the early stages of new technology adoption but diminishes at higher levels of adoption due to learning from experience.

In conclusion, contrary to static adoption analysis as in the conventional technology adoption literature, the dynamic adoption analysis approach could be a useful tool for identifying diverse subpopulation-level farmer needs for specific extension policies targeting farmers in those categories. The policy-specific targeting approach will save resources to expand extension outreach to benefit more farmers, thereby increasing productivity at least cost.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author on reasonable request.

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ENDNOTES

[1] Notable organizations that farmers identified include CSIR-SARI, IITA, and USAID-ADVANCE Project.

[2] In our calculation of the continuation value, we used *Weisbrod's* procedure, which uses the transition probability as the discount factor. This takes away the discretion of assuming any arbitrary discount factor which is hard to observe in reality compounded by the difficulty in assessing its heterogeneity among any group of decision-makers (Fagereng et al., 2020).

[3] This implies that the farmer at each stage of adoption is able to forecast the net benefits of the next stage.

[4] This specification does not assume any choice decision rules; therefore, it imposes neither rational expectation assumption nor forward-looking behavior on agents as in traditional discrete choice literature. Therefore, agents may be myopic, time inconsistent, and subjected to surprises (Heckman et al., 2016, 2018).

[5] We thank an anonymous reviewer for making this suggestion on the theoretical explanation of the decision-making mechanisms.

[6] *Fixed*, as used here, refers to constraining the farmer to a point (either 0 or 1) conditional on the farmer's further decisions along the adoption chain. This is necessary because a farmer who has made a further transition to a higher state will not be available to make a decision at the lower state. Therefore, fixing makes it possible to derive the counterfactual outcomes of not being at a particular state (see Heckman et al., 2016, 2018).

[7] First, $\boldsymbol{\theta}$correlates with the unobservable factors in the outcome equation as a result of heterogeneities in returns to farmers' wealth endowment, due to differences in the levels of investment in their scale of production and intensity of input use. We approximate this correlated effect in a linear-in-parameter factor model as $(U_s^k = \theta' \psi_s^k + \omega_s^k)$. Second, $\boldsymbol{\theta}$also correlates with the unobservable factors in the transitional choice decision due to inadequate financial ability to undertake further investment in the production cycle. This correlated effect is also approximated in a linear-in-parameter factor model as $(\eta_j = -(\theta' \lambda_j - \nu_j))$ (see Heckman et al., 2016, 2018, for more details).

[8] We do not intend to reproduce the full likelihood equation as captured in Heckman et al. (2016, 2018), so interested readers can refer to Heckman et al. (2016, 2018) for the full specification of the likelihood function as well as the measurement equation.

[9] The estimation codes for STATA implementation and other software requirements are publicly available at https://www.journals.uchicago.edu/doi/suppl/10.1086/698760 (see Heckman et al., 2018).

[10] The *direct effect* is the expected net benefits that accrue to a farmer for transiting to the next-adjacent adoption decision node such as from j to $j + 1$, whereas the *continuation effect* is the expected net benefits that accrue to a farmer for transiting beyond the next-adjacent adoption decision node such as transiting from j to $j + 1$ to $j + 2$ to $j + 3$, ..., to $j + l$.

[11] The AMTE is different from the local average treatment effect (LATE), in the sense that LATE is not defined for any specific margin of choice and also depends on the population of instrument compliers to measure the treatment effect.

[12] Farmers who use the inoculant only once are also considered as trial even without participation in field demonstration exercises.

[13] See the farmers' adoption decision tree in Appendix A1.

[14] The SCA is a standard practice in the dynamic discrete choice literature (Heckman et al., 2016, 2018).

[15] Majority of the farmers in our sample were indigenous land owners and not renters; therefore, this observation is consistent with the economic theory of owner-operated lands, as farmers have an incentive to maintain productivity of their lands into the future.

[16] Note that due to the disadvantages inherent in using onetime cross-sectional observation data in this analysis, the impact measures reported in this study do not represent causality. We thank an anonymous reviewer for this comment.

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[17] *Selection on gains* in this literature refers to a case where farmers who have higher or lower values of unobserved ability (i.e., unobserved factors, such as wealth endowment, that pose a resistance to a farmer to make a transition) to transit obtain higher-than-average (positive selection on gain) or lower-than-average (negative or reserve selection on gain) net benefits from making an adoption transition.

[18] See Appendixes A5, A6, and A7 for population- and subpopulation-level distributions, respectively.

[19] See Appendix A4 for mean plot of AMTE and ATE compared for both outcomes.

[20] Another important robustness check of the results that we are unable to perform due to data limitations (on pre-intervention factors) is the assumption of forward-looking behavior on the adoption state transition decisions of farmers, as often implicitly assumed in conventional dynamic optimization analysis. As such, the estimates reported in this study assumed implicitly that farmers may be prone to surprises and regrets in their adoption state transition decisions, though the approach employed in this study is robust to deviations from conventional decision rules by agents (Heckman et al., 2016). We are grateful to an anonymous reviewer for making this observation.

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