Heterogeneous Farmers' Technology Adoption Decisions: Good on Average Is Not Good Enough*

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Abstract

In spite of the importance of agriculture sector and the persistently low agricultural productivity, smallholders in Sub-Saharan Africa are unconcerned with the seemingly-profitable modern technology - fertilizer, and at the same time are keen on the seemingly-unbeneficial traditional technology - intercropping. This paper aims to solve that puzzle and understand the rationale behind farmers' decisions about agricultural technology adoption. I construct a farmer's decision-making model which takes into account both the expected value and the variance of a farmer's profit. Within this model, I build a farmer's production function that has three special properties: heterogeneous returns, selection bias, and heterogeneous variances for each technology. Estimating this structural model with the Tanzania Living Standards Measurement Study panel dataset, I discover that the expected returns of adopting the same technology vary significantly across farmers. Furthermore, adopting fertilizer significantly increases expected yields for farmers who adopt it every year, yet the higher expected returns are accompanied by larger variances. On the other hand, adopting intercropping does not increase the expected returns, but significantly decreases the variance of yields. Farmers' technology adoption decisions are influenced positively by the expected value of profits and negatively by the variance of profits. These empirical results explain the low adoption rates of an intensively promoted higher-average-return technology such as fertilizer, and justify the high adoption rates of a seemingly-unprofitable technology such as intercropping.

Keywords: Technology adoption, heterogeneity in return, selection bias, risk aversion.

1 Introduction

In Sub-Saharan African countries, the agriculture sector employs more than fifty percent of the total labor force and provides on average fifteen percent of total GDP (OECD-FAO, 2016). Despite the importance of agriculture sector, farmers in these countries persistently use traditional farming methods and face low agricultural productivity. Modern agricultural technologies offer high expected returns on average and have been widely adopted in developed countries, but they have been seldom used in Sub-Saharan Africa. Numerous studies have investigated and attempted to solve this conundrum. Various explanations are offered, such as lacking information, missing input markets, and liquidity constraints, yet there is no consensus on the justification. This paper aims to understand the rationale behind farmers' decisions about agricultural technology adoption. It examines a different hypothesis: farmers' decisions about adoption or non-adoption of modern technologies may be rational responses to the return distributions they face. Expected returns and variances differ across farmers and technologies. These differences could explain the variability in farmers' technology adoptions.

Within the literature about agricultural technology adoption, a large collection of studies focuses on the obstacles that have caused this insufficient usage, such as information failure (Foster and Rosenzweig, 1995; Munshi, 2004; Conley and Udry, 2010), supply shortages (Moser and Barrett, 2006), and credit constraints (Duflo et al., 2008). These studies implicitly assume that modern agricultural technologies are unambiguously better, and therefore non-adoption must be the result of some failures - a market failure or an information failure. While those factors contribute to the low and stagnating rate of technology adoption, they cannot fully account for it. After decades of technology promotion and rapid economic development, farmers have gained information on technologies and access to inputs. Yet, uptake of modern technologies remains low. One potential explanation for this is that adoption of modern technology may not be optimal for everyone (Suri, 2011; Liu, 2013). I examine this explanation and find results suggesting the assumption that low technology adoption is primarily driven by market failures may be incorrect.

This study contributes to the literature by constructing a model of farmer's decision-making which takes into account both the mean and the variance of a farmer's profits. Current literature about agricultural technology adoption is popularized with the expected return models. However, in economies with limited insurance, the fluctuations in profits also play crucial roles in farmers' decisions. Both the expectation and the variability of profits should be investigated. Furthermore, this paper borrows the concept of heterogeneity from labor economics (Carneiro and Lee, 2004; Heckman and Li, 2004). The model allows the effect on yield of adopting the same technology to be different across farmers and plots. In addition, farmers are assumed to have knowledge of their own productivity for each technology and choose which technology to adopt accordingly. Heterogeneous returns and selection bias are equally relevant in the decisions about agricultural technology adoption, but they have been understudied. This research attempts to fill in this gap, and relax the common assumptions in the literature that farmers are both homogeneous and risk-neutral expected value maximizers.

In my farmer's decision-making model, I assume that farmers are expected utility maximizers and may have preferences over both the mean and the variance of profits. At the beginning of each farming season, farmers choose one agricultural technology set to maximize their expected utility. They have four available choices: adopting nothing, adopting only inorganic fertilizer, adopting only intercropping, or adopting both fertilizer and intercropping. The core of farmer's decision making lays at farmer's production, which is substantially affected by his/her agricultural technology adoption choices. I construct the farmer's production function with three special properties: heterogeneous returns by farmer and technology, selection bias by farmer, and heterogeneous variances by technology. An important feature of my production model is that it allows farmers to consider multiple technologies at once, rather than binary adoption decisions in isolation.

Empirically, I estimate this farmer's decision-making model using the Tanzania Living

Standards Measurement Study (LSMS) panel dataset. I first evaluate the farmer's production function using a correlated random coefficient (CRC) model. Next, I solve the intrinsic characteristics of technology sets that affect the variance of productions through the feasible generalized least squares (FGLS) method, and then I re-estimate the farmer's production function with weights. Lastly, I calculate farmers' responses to both the expected value of profit and the variance of profit (risk aversion level), and analyze the factors that influence farmers' agricultural technology adoption decisions.

My results show that expected returns to technology adoption vary across different types of farmers and different technologies. Farmers are categorized into four groups based on their adoption histories - never-adopter, dis-adopter, late-adopter, and always-adopter. For farmers adopting only fertilizer and adopting both fertilizer and intercropping, the expected returns in yields are significantly larger than zero for farmers who adopt it in every year, aka always-adopters.[1] The estimated expected returns of always-adopter are higher than what a never-adopter would have achieved if he/she had adopted fertilizer or both technologies. This scenario indicates that farmers are rational, and many farmers do not adopt fertilizer because it would not significantly increase their yields given their own and their plot characteristics. In addition, the higher returns of adopting only fertilizer are accompanied by larger conditional variances of yields. On the other hand, compared to adopting nothing, the additional expected return of adopting only intercropping is approximately zero for every farmer. Nevertheless, adoption of intercropping leads to a significant reduction of the conditional variance of yields. Furthermore, adopting both technologies is not a simple summation of adopting only fertilizer and adopting only intercropping. This combination represents a different technology. Using the solved distributions of profits, I demonstrate that farmers respond positively to the expectation of profit and negatively to the variance of profit when they make their technology adoption choices. Even after controlling for other explanatory factors suggested in the literature on technology adoption, the influence of risk

[1] In this paper, I define "yield" as dollar values of outputs per acre.

is still important and significant in the farmer's decision-making process. When predicting farmer's probability of adopting each technology, if I set the variances of technologies to be zero, rather than their true values, the probability of adopting only fertilizer increases from 4% to 11%, while the probability of adopting only intercropping drops.

This paper designs and solves a structural model of farmer's technology adoption decision. This model is built to include five properties - heterogeneity in return, selection bias, heterogeneity in variance, mean-variance expected utility and multiple technologies, which are examined separately in the previous literature. The comprehensiveness of this model provides a better representation of the reality. With a precise understanding of farmers' rationale for agricultural technology adoption decisions, agricultural development policy-makers could target their policy prescriptions from various perspectives that affect farmers' expected utilities. For instance, policy-makers may reallocate spending away from less effective programs that spread more information about well-known technologies, and instead focus on insurance programs to nudge capable farmers from their rational low-mean and low-variance equilibrium to a better equilibrium, thereby improving farmer welfare.

2 Literature Review

This study is connected with three groups of literature: literature about agricultural technology diffusion and adoption in development economics, literature about heterogeneous returns to investment and self-selection behavior in labor economics, and literature about agricultural production in agricultural economics. It contributes to current work by constructing and solving a farmer's decision-making model through combining knowledge from multiple disciplines.

Reviewing the studies about technology adoption, the most renowned theme is about information failure, which leads to various learning models as solutions. Foster and Rosenzweig (1995) and Munshi (2004) both examine the adoption rates of high-yielding seed varieties in the Indian Green Revolution. Foster and Rosenzweig (1995) find evidence for both learning by doing and learning from others or social learning. Imperfect knowledge impedes farmers' adoption decisions. This dynamic improves as farmers accumulate experience, and the increases of both farmers' own experiences and neighbors' experiences significantly raise seed profitability and adoption. Munshi (2004) reaches a mixed result over different crops: wheat growers learn from neighbors' experiences, while rice growers benefit from own experiences. Along the social interaction line, Conley and Udry (2010) study the adoption of fertilizer for pineapple growing in Ghana, and suggest that there is social learning; farmers modify their input uses to align with their informative neighbors. Bandiera and Rasul (2006) investigate the adoption of sunflower in Mozambique, and find that farmers' behaviors are strongly correlated with their families' and friends' actions. The overarching takeaway for this cluster of studies is that technology adoption rates are likely to be low due to the lack of information. However, when farmers overcome information barriers, either from own experience or social experience, adoption is boosted. While information and learning have been the center of explanations for low adoption rates, these concepts become less influential nowadays, thanks to decades of technology promotions. In this research, I choose to study modern technologies which are well-known by farmers, so that information issue could be avoided.

The next commonly studied factors that hinder technology adoption are input scarcities, such as credit constraints and labor shortages. Moser and Barrett (2003) examine the adoption of the System of Rice Intensification (SRI) in Madagascar, and attribute the low adoption rate to additional labor requirements. When households have used their family labor and hired labor to the full capacity, seasonal liquidity constraints may exist if the modern technology requires extra labors. Croppenstedt et al. (2003) work on data about Ethiopia and find that lacking financial resources to buy fertilizer is one of the main reasons for non-adoption. Duflo et al. (2008) experiment with farmers in Western Kenya for fertilizer purchases, and realize that an effective commitment device at harvest period could increase the technology adoption rate by 11 to 14 percentage points. To reflect on the factor insufficiency issue, I select a couple technologies that require different inputs. Specifically, one technology would demand additional labors, and the other technology would request monetary resources.

Even though the adoption literature primarily focuses on reasons that have caused low adoption rates, a new strand of works appears with the null hypothesis that farmers make rational adoption decisions. Liu (2013) investigates the role of individual risk attitudes in the adoption decision of Bt cotton. Through a field experiment in China, she finds that farmers adopt the technology at different time because of their various risk preferences. Farmers who overweight small probabilities are the first adopters of Bt cotton, and farmers who have higher levels of risk aversion or loss aversion adopt Bt cotton later. Although the data which I use for this study do not measure risk preference explicitly, I estimate it from my expected utility function. Suri (2011) examines the heterogeneity in returns among farmers and finds that adopting a new technology may lead to large returns on average, but offer very low returns for marginal farmers. Using hybrid maize adoption data from Kenya, she discovers that farmers' decisions are rational - among the non-adopters, they either have approximately zero gross returns or face high costs, while adopters are farmers who enjoy positive returns and low costs.

In Suri (2011), she analyzes the impact of farmers' comparative advantage on their technology adoption and heterogeneous productions. While this approach is new to the agriculture setting, it has been more developed in the field of labor economics. For example, when examining the effect of schooling on wages, economists observe people's wages and education levels, but do not know about people's abilities and the reasons behind people's educational choices. Roy (1951) writes that individuals self-select into fishing or hunting, based on their own abilities. Lemieux (1998) finds that because of their comparative advantage across sectors, workers make corresponding decisions about choosing union jobs vs. non-union jobs. Card (1994) claims that there are heterogeneities in returns to education;

individuals understand that difference, know about their own abilities, and make their schooling choices accordingly. Similarly, Carneiro and Lee (2004) and Heckman and Li (2004) show that people self-select into college education, and the increase in lifetime earning due to college attendance is significantly higher for people who attend college than for people who do not attend college. To parallel the logic into agricultural study, one observes the revenues of farmers and their technology adoption decisions, but do not witnesses the rationale and the causal effect behind it. This study builds a farmer's production function with heterogeneous returns and self-selection features, and aims to decipher that unobserved rationale.

Furthermore, as Chavas and Pope (1982) suggest that models of agricultural production decisions under risks should always consider production uncertainty, I incorporate the riskiness of technology in my farmer's production function as the third feature. Pope and Just (1977) and Just and Pope (1979) propose a general stochastic specification for production function, so that the effects of input on output and the effects of input on variability of output could be different. I employ their recommended function form to examine the impact of technology use on risk. In addition to obtaining a variance component of the production function, my model further allows farmers to respond to the variance characteristics of technology in their expected utility functions, based on their risk attitude. Constructing a model that include all relevant traits, which have been studied separately in previous works, offers a more comprehensive and precise description of farmers' actions, and provides the instrument to investigate the reasoning behind farmers' behaviors.

3 Theoretical Model

Consider a rural village in the developing world. At the beginning of each farming season, farmers choose which agricultural technologies to adopt for each plot, among various existing technologies.

3.1 Agricultural Technology

To center the analysis on productivity and risk, I select the agricultural technologies following two criteria. First, I choose technologies which have existed and been promoted in the developing world for a significant amount of time, so that the information and learning effect could be limited. Secondly, for considering the diversification of modern technologies, I choose technologies which have different benefit distributions, i.e. mean and variance, and require distinct inputs. Specifically, I select two agricultural technologies: inorganic fertilizer (F) and intercropping (I). The rationale of selecting those particular technologies lays at the heterogeneity of farmers' preferences and the heterogeneity of technologies' characteristics. According to the literature (Day, 1965; Fuller, 1965; Horowitz and Lichtenberg, 1993; Piepho, 1998), fertilizer has potential to increase productions significantly, yet the benefits come with large production risks. On the other hand, intercropping is a technique which can reduce the variance of productions and improve the soil quality over time (Horwith, 1985).

In this paper, I concentrate on those two technologies. Nevertheless, they could be generalized to any technology. Also, regarding the benefit distribution of a specific technology, I focus on its mean and variance. This assumption could be justified from two angles. Either the profit function has a distribution which the knowledge of mean and variance are enough to describe the whole distribution, such as normal distribution, gamma distribution, and beta distribution; or farmers mainly care about those two perspectives of benefits, mean and variance. Future researches could expand the benefit distribution to include skewness, as farmers may have larger downside risk aversions.

3.2 Farmer's Decision-Making Model

At the beginning of each farming season, farmers choose the agricultural technology set that they want to adopt. Farmers could adopt nothing (N), only fertilizer (F), only intercropping (I), or both fertilizer and intercropping (B). Adopting both fertilizer and intercropping is considered a separate technology itself, which allows for more flexibility in the complementarity and substitutability of those two main technologies. From those four available choices, $D = \{N,\ F,\ I,\ B\}$, farmers pick one to achieve their goal, i.e. maximizing the expected utility. Let $h^D = \left\{h^N,\ h^F,\ h^I,\ h^B\right\}$ be the adoption set containing 4 dummy variables ($= 1$ or $= 0$), which indicate farmers' adoption decisions. After farmers decide the technology D, the values of all h^D are set. One, and only one, of those h^D must equal 1 while the others equal 0. For example, when farmers adopt only fertilizer, the model shows that $h^N = 0$, $h^F = 1$, $h^I = 0$, $h^B = 0$; when farmers adopt both fertilizer and intercropping, the model shows that $h^N = 0$, $h^F = 0$, $h^I = 0$, $h^B = 1$. Because each technology choice is exclusive to others, the sum of four dummy variables is always one.

Assume farmers are expected utility maximizers. Their levels of expected utility are affected by the production profit (π) - the expected profit (μ) and the variance of profit (v), and the influences of those two factors are determined by the marginal utility of profit (m) and the degree of risk aversion (ρ), as Equation 1:

$$\begin{aligned}
(1) \qquad \max_{h^N_{ijt},h^F_{ijt},h^I_{ijt},h^B_{ijt}} \quad EU_{ijt} &= m\mu_{ijt} + \rho v_{ijt} \\
s.t. \quad \mu_{ijt} &= \mathbb{E}[\pi_{ijt}] \\
v_{ijt} &= \mathbb{E}[(\pi_{ijt})^2] - (\mathbb{E}[\pi_{ijt}])^2,
\end{aligned}$$

where i represents farmer, j refers to plot, and t stands for agriculture season.[2] The choice variables, $\left\{h^N_{ijt},\ h^F_{ijt},\ h^I_{ijt},\ h^B_{ijt}\right\}$, are factors of the production profits (π). The unit of analysis is at the farmer-plot level (ij), due to the assumption that farmers make rational maximizing decisions for each plot individually, rather than strategically allocate their resources across all plots. If holding the belief that farmers enjoy high profits but suffer from a change of the profit level (risk averse), I predict the directions of those two indices as $m > 0$ and $\rho < 0$. The actual magnitudes and directions of those parameters are tested empirically.

Farmers' production profits (π) are determined by the gross revenue (Y) and the

[2]The unique identifier of data is at household-plot level. I address it as farmer-plot level for an easier interpretation of following analysis, with the belief that if a plot belongs to the same household over time, it is usually the same household member that plants it.

farming cost (C),

$$\pi_{ijt} = Y_{ijt} - C_{ijt}. \tag{2}$$

Both the gross revenue and the farming cost are affected by the agricultural technology adoption choices.

The total farming cost is a summation of two input costs - labor cost and fertilizer cost,

$$C^D_{ijt} = labor\ cost^D_{ijt} + fertilizer\ cost^D_{ijt}. \tag{3}$$

The farming cost has a simple linear functional form and varies by the technology.

Assume the farmer's production function has a Cobb-Douglas form. I define the farmer's production function of a plot under a particular technology set (D) as in Equation 4. Farmer's revenues are affected by 3 components: 1) a technology-specific aggregate returns to revenue, β^D, which could be thought as a combination of the macroeconomic factors and the characteristics of the agricultural technology set that affect the average revenues, 2) k exogenous observable farming inputs (X), such as precipitation amounts and temperature levels, 3) a technology-specific error (u^D) , including time-invariant unobservable farmer and technology characteristics, and time-varying random production shocks. Taking logs of Equation 4, I get Equation 5, where y_{ijt} is the log of revenue, and other variables are redefined to stand the logs of their corresponding variables.

$$Y^D_{ijt} = e^{\beta^D_t}(\prod_{m=1}^{k} X^{\gamma_m}_{ijtm})e^{(u^D_{ijt})} \tag{4}$$

$$y^D_{ijt} = \beta^D_t + \boldsymbol{x_{ijt}}'\boldsymbol{\gamma} + u^D_{ijt}, \tag{5}$$

where $\boldsymbol{x}_{ijt}$ is a vector with dimension $k \times 1$, $\boldsymbol{\gamma}$ is a vector of the output elasticity of farming inputs. Assume the gross yield (Y) follows a lognormal distribution, and thus the log of yield (y) follows a normal distribution.

A point to note, in the current model set-up, I contribute both the extra quantity of inputs required by a particular technology set and their associated input intensity effects to the technology-specific aggregate returns component, counting those impacts as the technology attribute which affects the mean of revenues (β^D); $\boldsymbol{\gamma}$ is not technology-specific. In addition, the yield variables are expressed as ratios of the land size, i.e. per acre. Farmers would produce only when their expected profits are not negative.

For simplicity, I make two assumptions in this model. Firstly, there is no risk sharing or strategical cooperation in the village. Farmers make their own decisions based on their unique situations and are not influenced by their neighbors' experience. Secondly, because the farming inputs and crops choices are not the focus of this paper, I assume that once a farmer chooses the technology he/she would like to use, the other inputs are predetermined. For example, if he/she chooses intercropping, that implies a set amount of labor input. In addition, the agricultural yields are presented as monetary values, so that the types of crops are less relevant.[3] The outcome variable could be perceived as one scalar, rather than a vector of various crop productions.

3.3 Farmer's Production Function

The core of farmers' decision making lays at farmers' productions; while farmers' revenues are substantially affected by their agricultural technology adoption choices. To study the impact of technology adoption, I follow the methodology in labor economics and put additional structure into the production function. When examining the effect of education on wages, labor economists state two important issues needed to be considered: 1) returns to schooling are heterogeneous in the population, 2) the unobservable ability in the residual term is correlated with the regressor - schooling, as individuals know their abilities and choose their education levels accordingly. Analogously, one could suspect that the effects of adopting the same technology on revenues are different across farmers and plots. More importantly, farmers may have good estimations of their productivity of each technology and choose the adoption accordingly. In the following two sub-sections, I present these two properties in my production function.

[3]The influences of crop choices on technology adoptions are examined in the robustness checks section.

3.3.1 Heterogeneity in Return

Equation 5 shows a farmer's production function of adopting a specific technology set. In each farming season, farmers could adopt any agricultural technology, the observed revenue could be written as below,

$$
\begin{aligned}
(6) \qquad\qquad y_{ijt} &= \sum_D h^D_{ijt} y^D_{ijt} \\
&= h^F_{ijt}[\beta^F_t + \boldsymbol{x}_{ijt}\boldsymbol{\gamma} + u^F_{ijt}] + h^I_{ijt}[\beta^I_t + \boldsymbol{x}_{ij}\boldsymbol{\gamma} + u^I_{ijt}] \\
&\quad + h^B_{ijt}[\beta^B_t + \boldsymbol{x}_{ijt}\boldsymbol{\gamma} + u^B_{ijt}] + (1 - h^F_{ijt} - h^I_{ijt} - h^B_{ijt})[\beta^N_t + \boldsymbol{x}_{ijt}\boldsymbol{\gamma} + u^N_{ijt}] \\
(7) \qquad \Rightarrow \quad y_{ijt} &= \beta^N_t + \boldsymbol{x}_{ijt}\boldsymbol{\gamma} + [(\beta^F_t - \beta^N_t) + (u^F_{ijt} - u^N_{ijt})]h^F_{ijt} \\
&\quad + [(\beta^I_t - \beta^N_t) + (u^I_{ijt} - u^N_{ijt})]h^I_{ijt} + [(\beta^B_t - \beta^N_t) + (u^B_{ijt} - u^N_{ijt})]h^B_{ijt} + u^N_{ijt}.
\end{aligned}
$$

Examining the three coefficients placed in front of the adoption dummies, $[(\beta^F_t - \beta^N_t) + (u^F_{ijt} - u^N_{ijt})]$, $[(\beta^I_t - \beta^N_t) + (u^I_{ijt} - u^N_{ijt})]$, $[(\beta^B_t - \beta^N_t) + (u^B_{ijt} - u^N_{ijt})]$, they represent the returns to adopting only fertilizer, adopting only intercropping, and adopting both technologies, respectively. Because all three coefficients include a $u^D_{ijt} - u^N_{ijt}$ term, which varies at the farmer-plot level (ij), the production function has the feature of heterogeneous return: rewards of each agricultural technology are farmer-plot-specific. Returns are random variables with distributions. Estimating Equation 7 requires a random coefficient model.

3.3.2 Selection Bias in Adoption and Uncertainty of Production

To analyze the unobserved heterogeneity and the uncertainty of production deeper, I decompose the technology-specific error terms into two parts: productivity and shock. I put additional structure on those two parts. For each farmer, he/she always has a general farming productivity (θ_{ij}); if he/she adopts any technology, he/she also has a second productivity component in term of that technology (θ^D_{ij}). For the shock term, I assume that there is an individual level idiosyncratic shock (ε), such as $E(\varepsilon) = 0$ and $V(\varepsilon) = 1$. More importantly, the level of shock is amplified by a characteristic of the adopted technology (α^D), which captures the variability of yields across different technologies. This multiplicative setup of the shock term follows the concept of Just-Pope production function model (1977), to allow distinct effects between the effect of technology on output and the effect of technology on variability of output. The technology-specific production functions are modified as below:

$$y^N_{ijt} = \beta^N_t + \boldsymbol{x}_{ijt}\boldsymbol{\gamma} + \theta_{ij} + (\alpha^N)^{\frac{1}{2}}\varepsilon_{ijt} \tag{8}$$

$$y^F_{ijt} = \beta^F_t + \boldsymbol{x}_{ijt}\boldsymbol{\gamma} + \theta_{ij} + \theta^F_{ij} + (\alpha^F)^{\frac{1}{2}}\varepsilon_{ijt} \tag{9}$$

$$y^I_{ijt} = \beta^I_t + \boldsymbol{x}_{ijt}\boldsymbol{\gamma} + \theta_{ij} + \theta^I_{ij} + (\alpha^I)^{\frac{1}{2}}\varepsilon_{ijt} \tag{10}$$

$$y^B_{ijt} = \beta^B_t + \boldsymbol{x}_{ijt}\boldsymbol{\gamma} + \theta_{ij} + \theta^B_{ij} + (\alpha^B)^{\frac{1}{2}}\varepsilon_{ijt}. \tag{11}$$

Rewritten the observed revenue using elaborated production functions,

$$\begin{aligned} y_{ijt} &= \sum_D h^D_{ijt} y^D_{ijt} \\ &= \beta^N_t + \boldsymbol{x}_{ijt}\boldsymbol{\gamma} + (\beta^F_t - \beta^N_t)h^F_{ijt} + (\beta^I_t - \beta^N_t)h^I_{ijt} + (\beta^B_t - \beta^N_t)h^B_{ijt} \\ &\quad + \theta_{ij} + \theta^F_{ij}h^F_{ijt} + \theta^I_{ij}h^I_{ijt} + \theta^B_{ij}h^B_{ijt} + \varepsilon_{ijt}\{(\alpha^N)^{\frac{1}{2}} \\ &\quad + [(\alpha^F)^{\frac{1}{2}} - (\alpha^N)^{\frac{1}{2}}]h^F_{ijt} + [(\alpha^I)^{\frac{1}{2}} - (\alpha^N)^{\frac{1}{2}}]h^I_{ijt} + [(\alpha^B)^{\frac{1}{2}} - (\alpha^N)^{\frac{1}{2}}]h^B_{ijt}\} \\ &= \beta^N_t + \boldsymbol{x}_{ijt}\boldsymbol{\gamma} + \theta_{ij} + [(\beta^F_t - \beta^N_t) + \theta^F_{ij}]h^F_{ijt} \\ &\quad + [(\beta^I_t - \beta^N_t) + \theta^I_{ij}]h^I_{ijt} + [(\beta^B_t - \beta^N_t) + \theta^B_{ij}]h^B_{ijt} + \varepsilon_{ijt}\{(\alpha^N)^{\frac{1}{2}} \\ &\quad + [(\alpha^F)^{\frac{1}{2}} - (\alpha^N)^{\frac{1}{2}}]h^F_{ijt} + [(\alpha^I)^{\frac{1}{2}} - (\alpha^N)^{\frac{1}{2}}]h^I_{ijt} + [(\alpha^B)^{\frac{1}{2}} - (\alpha^N)^{\frac{1}{2}}]h^B_{ijt}\}. \end{aligned} \tag{12}$$

Looking at the three coefficients placed in front of the adoption dummies again, $(\beta^F_t - \beta^N_t) + \theta^F_{ij}$, $(\beta^I_t - \beta^N_t) + \theta^I_{ij}$, $(\beta^B_t - \beta^N_t) + \theta^B_{ij}$, they are returns to technology adoption, including an observed aggregate return term, and an unobserved productivity term. Because farmers' adoption decisions (h^D_{ijt}) and their expected profits (π_{ijt}) are tied together as in Equation 1, and farmers' productivity (θ^D_{ij}) and their production outputs (y_{ijt}), thus their expected profits (π_{ijt}), are correlated as in Equation 12, farmers' productivity (θ^D_{ij}) and farmers' adoption decisions (h^D_{ijt}) are mutually related too. Given part of the coefficient on h^D_{ijt}, parameter θ^D_{ij}, is correlated with the independent variable h^D_{ijt}, the empirical analysis should be carried out through a correlated random coefficient model with a control function.

3.4 Variability of Farmer's Production Function

For simplification, I make some redefining definitions, as below:

(13) $\beta_t^d - \beta_t^N \equiv \tilde{\beta}^d \quad \forall d,\ d \in D,\ d \neq N\ and\ \forall t$

(14) $\varepsilon_{ijt}\{(\alpha^N)^{\frac{1}{2}} + [(\alpha^F)^{\frac{1}{2}} - (\alpha^N)^{\frac{1}{2}}]h_{ijt}^F + [(\alpha^I)^{\frac{1}{2}} - (\alpha^N)^{\frac{1}{2}}]h_{ijt}^I + [(\alpha^B)^{\frac{1}{2}} - (\alpha^N)^{\frac{1}{2}}]h_{ijt}^B\} \equiv e_{ijt}.$

Equation 13 indicates that the difference in aggregate returns to revenues between adopting nothing and adopting some technology are constant over time; while the base, the aggregate returns to revenues of adopting nothing can be varied over time due to macroeconomic and environment conditions. Equation 14 is for the purpose of an easier writing. The observed farmer production function becomes,

(15) $y_{ijt} = \beta_t^N + \boldsymbol{x}_{ijt}\boldsymbol{\gamma} + \tilde{\beta}^F h_{ijt}^F + \tilde{\beta}^I h_{ijt}^I + \tilde{\beta}^B h_{ijt}^B + \theta_{ij} + \theta_{ij}^F h_{ijt}^F + \theta_{ij}^I h_{ijt}^I + \theta_{ij}^B h_{ijt}^B + e_{ijt}.$

Unlike most of traditional production functions, I do not assume a priori an unified influence of technology adoptions on the mean and the variance of yields. From the farmer's production function, Equation 15, I obtain the variance of yield,[4]

$$
\begin{aligned}
(16)\ Var\{y_{ijt}\} &= \boldsymbol{\gamma^2} var\{\boldsymbol{x}_{ijt}\} + (\tilde{\beta}^F)^2 Var\{h_{ijt}^F\} + (\tilde{\beta}^I)^2 Var\{h_{ijt}^I\} + (\tilde{\beta}^B)^2 Var\{h_{ijt}^B\} \\
&\quad + Var\{\theta_{ij}\} + Var\{\theta_{ij}^F h_{ijt}^F\} + Var\{\theta_{ij}^I h_{ijt}^I\} + Var\{\theta_{ij}^B h_{ijt}^B\} + Var\{e_{ijt}\}.
\end{aligned}
$$

3.5 Summary

To sum up, in each farming season, farmers choose the adoption of a technology to maximize their expected utilities, which are affected by the expected value of profits and the variance of profits. The expected profits depend on the technology adopted and farmer-specific productivity, thus vary by both the technology and the farmer. The variances of profits depend on the technology adopted and the random shock, hence in expectation only vary by the technology. Based on the characteristics of technologies, farmers' technology-specific productivity, and farmers' responses to the profit value and the risk level, farmers make individual adoption decisions.

[4] The detailed steps for obtaining the variance of yield are in Appendix B.

4 Data

The dataset employed by this research is the Tanzania National Panel Survey (TZNPS), which is part of the World Bank Living Standards Measurement Study (LSMS). It is a nationally-representative integrated household survey. It is repeated biennially and has four waves: 2008-2009, 2010-2011, 2012-2013, and 2014-2015. In this paper, I use the middle two waves of data, 2010-2011 round and 2012-2013 round, since they use more similar questionnaires and have more overlapping samples. The Tanzania National Panel Survey covers a broad range of topics. The main subjects I concentrated on are its extensive information of households' farming practices and demographic characteristics.

4.1 Household and Plot Characteristics

The TZNPS sampled 26 regions out of 31 regions of Tanzania, aiming to be representative for the whole country. In round 1 (2008-2009), it surveyed 125 districts, 337 enumeration areas/villages, 3265 households, and 5152 plots. In the following rounds, all original households were revisited and re-interviewed. If any adult members have moved to other locations, they were all tracked and re-interviewed at current locations with their new households. Because of the splitting off, in round 2 (2010-2011), the survey contained 129 districts, 368 enumeration areas/villages, 3924 households, and 6038 plots; in round 3 (2012-2013), the survey covered 132 districts, 384 enumeration areas/villages, 5010 households, and 7457 plots.[5] In all later (non-first) rounds of data, the surveys included unique household and plot identifiers of both the current round and the previous round. Thus, if the household or the plot have been interviewed before, I could match them across data rounds.

For all data analysis, I use a balanced panel constructed from round 2 and round 3 data. The reason for a balanced panel is that estimating my structural model requires knowing farmers' adoption choices of all years. In each year, about 80% of plots were

[5] The data expansion across rounds is relative huge comparing to other studies; but this pattern is verified both by the survey documents and the dataset.

cultivated, 10-15% of plots were fallow, and the rest of plots were rented out, given out, forest, or in other use. Moreover, among the cultivated plots, 5% of plots were not harvested due to destruction (3%), still growing in plot (1%), and other reasons (1%), when the interviews were conducted. Limiting the sample to plots that have been cultivated and harvested in both rounds, there are 1638 households and 2539 plots.[6] I further restrict the sample to observations with non-missing values for all variables used in the analysis, and end up with 1628 households and 2523 plots, aka the analysis sample.

Table 1 presents the descriptive statistics of sampled households. Around 87% of households located at rural area, yet some urban households cultivated plots in the long rainy season as well. Most of households had male heads, about 77%. Roughly 85% of household heads had the main occupation in agriculture, while other household members could be in charge of the household farming too. The average family size was 5.8, including 3.3 active members (age 12-60) and 2.5 dependents (children and elders). The average annual temperature was about 22.6°C; and the average annual rainfall in the past 12 months was round 800 mm.

Table 2 describes the characteristics of plots. On average, plots were 2.9 acres, had above average soil quality where 1 stands for bad quality and 3 stands for good quality, and medium steepness where 1 stands for flat and 3 stands for very steep. Very few plots (4%) had been fallowed before[7]; while approximately 75% of plots could be sold by their belonging households. Each plot usually used 64 days per acre of family labor, with helps from hired labors that were worth 6 dollar per acre. Also, around 1 dollar worth of pesticides were applied on the plot. Lastly, the harvest amounts were about 124 dollars per acre.[8]

[6] The sample size has dropped significantly because in each year, different plots got fallow and happened to be not harvested. The accumulation of rotated 24% ($= 1 - 80\% \times 95\%$) has resulted a large amount.

[7] This low rate could be due to my selection of plots that were not fallowed in both farming season 2010-2011 and farming season 2012-2013.

[8] These harvest values are farmers' self-reported estimated values of their harvests. Given that farmers may have different perceptions for crop prices, later I will create another harvest value variable using reported harvest quantities (kg), and village prices and/or district prices as robustness checks.

4.2 Farming Practices

Table 3, a transition matrix of farmers' adoptions, shows descriptive statistics of farmers' adoption of the four exclusive agricultural technology mentioned in Section 3.2, at the farmer-plot level. Across the two farming seasons, the percentages of technology adoptions at farmer-plot level were stable. There were approximately 37.6%-39.5% of plots adopted neither technology, 7.8%-8.0% of plots adopted only fertilizer, 44.1%-45.6% of plots adopted only intercropping, and 8.6%-8.8% of plots adopted both technologies. Nevertheless, if reading the diagonal of Table 3, one could see that only 58.5% of plots adopted the same technology across two years, and the other half of plots experienced different technologies over time. The technology switching behaviors of farmers are essential for the structural model estimation, i.e. creating the counterfactual.

5 Empirical Strategy

To empirically study farmers' decisions about agricultural technology adoption, I estimate the farmer's decision-making model through four parts. In the first step, I evaluate the farmer's production function as a correlated random coefficient (CRC) model, and substitute farmer's unobservable and endogenous productivity with its linear projection on the farmer's full history of adoptions and their interactions. In the second step, I decompose the previously estimated residual term of farmer's production function through the feasible generalized least squares (FGLS) method. Thus, I separate out the intrinsic characteristic of technology set that affects the variance of productions. Then, I re-estimate the production function with a weight derived from the previous step, thus all coefficients are updated to be both consistent and asymptotic efficient. Lastly, I bring the estimated production values back into the farmer's expected utility function. Using the alternative-specific conditional logit method, I calculate farmers' responses to the expected value of profit and the variance of profit, and analyze factors that influence farmers' technology adoption decisions.

5.1 Estimate the Farmer's Production

I estimate the farmer's production function using a correlated random coefficient model, for addressing heterogeneous returns and selection bias.

Equation 15 is my main empirical specification. To eliminate the dependence between the farmer's productivity (θ) and their endogenous adoption decisions (h), I follow the idea of Chamberlain (1984) and Suri (2011), and replace the unobservable θ with its linear projection on the farmer's full history of adoptions and their interactions. As there are two periods in the dataset, the linear projection for each technology-specific productivity and general farming productivity are defined as following:

$$\theta_{ij}^F = \lambda_0^F + \lambda_1^F h_{ij1}^F + \lambda_2^F h_{ij2}^F + \lambda_3^F h_{ij1}^F h_{ij2}^F + \nu_{ij}^F \tag{17}$$

$$\theta_{ij}^I = \lambda_0^I + \lambda_1^I h_{ij1}^I + \lambda_2^I h_{ij2}^I + \lambda_3^I h_{ij1}^I h_{ij2}^I + \nu_{ij}^I \tag{18}$$

$$\theta_{ij}^B = \lambda_0^B + \lambda_1^B h_{ij1}^B + \lambda_2^B h_{ij2}^B + \lambda_3^B h_{ij1}^B h_{ij2}^B + \nu_{ij}^B \tag{19}$$

$$\begin{aligned} \theta_{ij} = {} & \lambda_0^N + \lambda_1^N (1 - h_{ij1}^F - h_{ij1}^I - h_{ij1}^B) + \lambda_2^N (1 - h_{ij2}^F - h_{ij2}^I - h_{ij2}^B) \\ & + \lambda_3^N (1 - h_{ij1}^F - h_{ij1}^I - h_{ij1}^B)(1 - h_{ij2}^F - h_{ij2}^I - h_{ij2}^B) + \nu_{ij}^N. \end{aligned} \tag{20}$$

In addition, I normalize all productivities, so that $\sum_n \theta_{ij}^F = 0$, $\sum_n \theta_{ij}^I = 0$, $\sum_n \theta_{ij}^B = 0$, and $\sum_n \theta_{ij} = 0$, where n stands for the number of observations (farmer-plot) in the sample.

Substituting all linear projections, Equation 17 - 20, into the production function, Equation 15, and writing it out period by period, I obtain the structural equations, Equation

21 - 22.

$$\begin{aligned}
(21)\quad y_{ij1} &= (\beta_1^N + \lambda_0^N + \lambda_1^N + \lambda_2^N + \lambda_3^N) + \boldsymbol{x}_{ij1}\boldsymbol{\gamma} \\
&+ (\tilde{\beta}^F + \lambda_0^F + \lambda_1^F - \lambda_1^N - \lambda_3^N)h_{ij1}^F - (\lambda_2^N + \lambda_3^N)h_{ij2}^F + (\lambda_2^F + \lambda_3^F + \lambda_3^N)h_{ij1}^F h_{ij2}^F \\
&+ (\tilde{\beta}^I + \lambda_0^I + \lambda_1^I - \lambda_1^N - \lambda_3^N)h_{ij1}^I - (\lambda_2^N + \lambda_3^N)h_{ij2}^I + (\lambda_2^I + \lambda_3^I + \lambda_3^N)h_{ij1}^I h_{ij2}^I \\
&+ (\tilde{\beta}^B + \lambda_0^B + \lambda_1^B - \lambda_1^N - \lambda_3^N)h_{ij1}^B - (\lambda_2^N + \lambda_3^N)h_{ij2}^B + (\lambda_2^B + \lambda_3^B + \lambda_3^N)h_{ij1}^B h_{ij2}^B \\
&+ \lambda_3^N h_{ij1}^F h_{ij2}^I + \lambda_3^N h_{ij1}^F h_{ij2}^B + \lambda_3^N h_{ij1}^I h_{ij2}^F + \lambda_3^N h_{ij1}^I h_{ij2}^B + \lambda_3^N h_{ij1}^B h_{ij2}^F + \lambda_3^N h_{ij1}^B h_{ij2}^I \\
&+ \nu_{ij}^N + \nu_{ij}^F h_{ij1}^F + \nu_{ij}^I h_{ij1}^I + \nu_{ij}^B h_{ij1}^B + e_{ij1} \\
(22)\quad y_{ij2} &= (\beta_2^N + \lambda_0^N + \lambda_1^N + \lambda_2^N + \lambda_3^N) + \boldsymbol{x}_{ij2}\boldsymbol{\gamma} \\
&- (\lambda_1^N + \lambda_3^N)h_{ij1}^F + (\tilde{\beta}^F + \lambda_0^F + \lambda_2^F - \lambda_2^N - \lambda_3^N)h_{ij2}^F + (\lambda_1^F + \lambda_3^F + \lambda_3^N)h_{ij1}^F h_{ij2}^F \\
&- (\lambda_1^N + \lambda_3^N)h_{ij1}^I + (\tilde{\beta}^I + \lambda_0^I + \lambda_2^I - \lambda_2^N - \lambda_3^N)h_{ij2}^I + (\lambda_1^I + \lambda_3^I + \lambda_3^N)h_{ij1}^I h_{ij2}^I \\
&- (\lambda_1^N + \lambda_3^N)h_{ij1}^B + (\tilde{\beta}^B + \lambda_0^B + \lambda_2^B - \lambda_2^N - \lambda_3^N)h_{ij2}^B + (\lambda_1^B + \lambda_3^B + \lambda_3^N)h_{ij1}^B h_{ij2}^B \\
&+ \lambda_3^N h_{ij1}^F h_{ij2}^I + \lambda_3^N h_{ij1}^F h_{ij2}^B + \lambda_3^N h_{ij1}^I h_{ij2}^F + \lambda_3^N h_{ij1}^I h_{ij2}^B + \lambda_3^N h_{ij1}^B h_{ij2}^F + \lambda_3^N h_{ij1}^B h_{ij2}^I \\
&+ \nu_{ij}^N + \nu_{ij}^F h_{ij2}^F + \nu_{ij}^I h_{ij2}^I + \nu_{ij}^B h_{ij2}^B + e_{ij2.}
\end{aligned}$$

Because the coefficients of structural equations could not be directly identified, I write out the corresponding reduced forms, Equation 23 - 24.

$$\begin{aligned}
(23)\quad y_{ij1} &= \kappa_1 + \boldsymbol{x}_{ijt}\boldsymbol{\gamma} + \eta_1 h_{ij1}^F + \eta_2 h_{ij2}^F + \eta_3 h_{ij1}^F h_{ij2}^F \\
&+ \eta_4 h_{ij1}^I + \eta_5 h_{ij2}^I + \eta_6 h_{ij1}^I h_{ij2}^I + \eta_7 h_{ij1}^B + \eta_8 h_{ij2}^B + \eta_9 h_{ij1}^B h_{ij2}^B \\
&+ \eta_{10} h_{ij1}^F h_{ij2}^I + \eta_{11} h_{ij1}^F h_{ij2}^B + \eta_{12} h_{ij1}^I h_{ij2}^F + \eta_{13} h_{ij1}^I h_{ij2}^B \\
&+ \eta_{14} h_{ij1}^B h_{ij2}^F + \eta_{15} h_{ij1}^B h_{ij2}^I + \varsigma_{ij1} \\
(24)\quad y_{ij2} &= \kappa_2 + \boldsymbol{x}_{ijt}\boldsymbol{\gamma} + \eta_{16} h_{ij1}^F + \eta_{17} h_{ij2}^F + \eta_{18} h_{ij1}^F h_{ij2}^F \\
&+ \eta_{19} h_{ij1}^I + \eta_{20} h_{ij2}^I + \eta_{21} h_{ij1}^I h_{ij2}^I + \eta_{22} h_{ij1}^B + \eta_{23} h_{ij2}^B + \eta_{24} h_{ij1}^B h_{ij2}^B \\
&+ \eta_{25} h_{ij1}^F h_{ij2}^I + \eta_{26} h_{ij1}^F h_{ij2}^B + \eta_{27} h_{ij1}^I h_{ij2}^F + \eta_{28} h_{ij1}^I h_{ij2}^B \\
&+ \eta_{29} h_{ij1}^B h_{ij2}^F + \eta_{30} h_{ij1}^B h_{ij2}^I + \varsigma_{ij2.}
\end{aligned}$$

Several variables are redefined in the process for simplification:

$$\kappa_1 = \beta_1^N + \lambda_0^N + \lambda_1^N + \lambda_2^N + \lambda_3^N \tag{25}$$

$$\kappa_2 = \beta_2^N + \lambda_0^N + \lambda_1^N + \lambda_2^N + \lambda_3^N \tag{26}$$

$$\varsigma_{ij1} = \nu_{ij}^N + \nu_{ij}^F h_{ij1}^F + \nu_{ij}^I h_{ij1}^I + \nu_{ij}^B h_{ij1}^B + e_{ij1} \tag{27}$$

$$\varsigma_{ij2} = \nu_{ij}^N + \nu_{ij}^F h_{ij2}^F + \nu_{ij}^I h_{ij2}^I + \nu_{ij}^B h_{ij2}^B + e_{ij2.} \tag{28}$$

Using 30 reduced form parameters (η_1-η_{30}), I can solve 19 structural parameters (λ_0^F, λ_1^F, λ_2^F, λ_3^F, λ_0^I, λ_1^I, λ_2^I, λ_3^I, λ_0^B, λ_1^B, λ_2^B, λ_3^B, λ_0^N, λ_1^N, λ_2^N, λ_3^N,$\tilde{\beta}^F$, $\tilde{\beta}^I$, $\tilde{\beta}^B$). Given that each λ_0^D could be written as a function of λ_1^D , λ_2^D , and λ_3^D , I eliminate all four λ_0^D, and only need to estimate 15 structural parameters (λ_1^F, λ_2^F, λ_3^F, λ_1^I, λ_2^I, λ_3^I, λ_1^B, λ_2^B, λ_3^B, λ_1^N, λ_2^N, λ_3^N,$\tilde{\beta}^F$, $\tilde{\beta}^I$, $\tilde{\beta}^B$).

The detailed estimation steps are as follows. Firstly, I estimate the reduced form equations, Equation 23 - 24, as a set of seemingly unrelated regressions. I save 30 reduced form parameters in a vector $R_{[30\times1]}$, and preserve the variance-covariance matrices from those 2 equations into 1 block matrix $V_{[30\times30]}$. Then, because of the restrictions on parameters between the structural equations and reduced forms, I require $R = H\psi$, where $H_{[30\times15]}$ is the restriction matrix listed in Appendix A, and $\psi_{[15\times1]}$ is the vector of 15 structural parameters. Last, I employ the optimal minimum distance (OMD) method to solve the structural parameters ψ,

$$\min_\psi = \{R - H\psi\}' V^{-1} \{R - H\psi\} \tag{29}$$

$$\Rightarrow \quad \psi^* = (H'V^{-1}H)^{-1} H'V^{-1}R. \tag{30}$$

The standard errors and confidence intervals of structural parameters are estimated through bootstrap. I draw 3100 random samples with replacement from the analysis sample, with stratified at the rural/urban level and clustered at the cluster level, i.e. the village for rural areas and the enumeration area for urban areas. The actual number of iterations (T) used for creating statistics depend on the number of converged sample. The calculation formulas for standard errors are listed below (Hansen, 2015), using β as an example,

$$\bar{\beta}^* = \frac{1}{T}\sum_{b=1}^{T}\hat{\beta}_b^* \tag{31}$$

$$\widehat{se(\hat{\beta})} = \sqrt{\frac{1}{T-1}\sum_{b=1}^{T}(\hat{\beta}_b^* - \bar{\beta}^*)}. \tag{32}$$

The calculation formula for confidence intervals is following (Hansen, 2015), using β as an example,

$$CI = [\hat{\beta} - q_T^*(1-\alpha/2), \quad \hat{\beta} - q_T^*(\alpha/2)], \tag{33}$$

where $q_T^*(\alpha)$ is the quantile function of the bootstrap distribution, $F_T(\hat{\beta}_b^*) = \hat{\beta} - \hat{\beta}_b^*$, and α is the chosen significance level.

5.2 Estimate the Variability of Farmer's Production

It is important to understand the impact of agricultural technology on both the mean and the variance of yields. So I estimate the variability of yields as follows.

Following the variance of yield (Equation 16), given a selected data sample, I can write the conditional variance of yields,[9]

$$Var\{y_{ijt}|\boldsymbol{x}_{ijt}, h_{ijt}^D\} = Var\{e_{ijt}|\boldsymbol{x}_{ijt}, h_{ijt}^D\}. \tag{34}$$

Recall e_{ijt} is the error term of the structural model. Revisit Equation 14, where I have defined e_{ijt},

$$\begin{aligned} e_{ijt} &= \varepsilon_{ijt}\{(\alpha^N)^{\frac{1}{2}} + [(\alpha^F)^{\frac{1}{2}} - (\alpha^N)^{\frac{1}{2}}]h_{ijt}^F + [(\alpha^I)^{\frac{1}{2}} - (\alpha^N)^{\frac{1}{2}}]h_{ijt}^I + [(\alpha^B)^{\frac{1}{2}} - (\alpha^N)^{\frac{1}{2}}]h_{ijt}^B\} \\ &= \varepsilon_{ijt}\{(\alpha^N)^{\frac{1}{2}}(1 - h_{ijt}^F - h_{ijt}^I - h_{ijt}^B) + (\alpha^F)^{\frac{1}{2}}h_{ijt}^F + (\alpha^I)^{\frac{1}{2}}h_{ijt}^I + (\alpha^B)^{\frac{1}{2}}h_{ijt}^B\} \\ &= \sum_{d\in D}(\alpha^d)^{\frac{1}{2}}h_{ijt}^d\varepsilon_{ijt}. \end{aligned} \tag{35}$$

Substituting it into Equation 34, I have

$$\begin{aligned} & Var\{y_{ijt}|\boldsymbol{x}_{ijt}, h_{ijt}^D\} = Var\{e_{ijt}|\boldsymbol{x}_{ijt}, h_{ijt}^D\} \\ = \; & E[\alpha^N h_{ijt}^N|\boldsymbol{x}_{ijt}, h_{ijt}^D] + E[\alpha^F h_{ijt}^F|\boldsymbol{x}_{ijt}, h_{ijt}^D] + E[\alpha^I h_{ijt}^I|\boldsymbol{x}_{ijt}, h_{ijt}^D] + E[\alpha^B h_{ijt}^B|\boldsymbol{x}_{ijt}, h_{ijt}^D]. \end{aligned} \tag{36}$$

[9] The detailed steps for obtaining the conditional variance of yield are in Appendix B.

In addition, by the definition of variance, I know,

$$(37) \qquad Var\{e_{ijt}|\boldsymbol{x}_{ijt}, h^D_{ijt}\} = E[e^2_{ijt}|\boldsymbol{x}_{ijt}, h^D_{ijt}] - E[e_{ijt}|\boldsymbol{x}_{ijt}, h^D_{ijt}]^2 = E[e^2_{ijt}|\boldsymbol{x}_{ijt}, h^D_{ijt}].$$

Combining Equation 36 and Equation 37 together,

$$(38) \qquad \begin{aligned} Var\{y_{ijt}|\boldsymbol{x}_{ijt}, h^D_{ijt}\} &= Var\{e_{ijt}|\boldsymbol{x}_{ijt}, h^D_{ijt}\} \\ &= E[e^2_{ijt}|\boldsymbol{x}_{ijt}, h^D_{ijt}] \\ &= E[\alpha^N h^N_{ijt}|\boldsymbol{x}_{ijt}, h^D_{ijt}] + E[\alpha^F h^F_{ijt}|\boldsymbol{x}_{ijt}, h^D_{ijt}] + E[\alpha^I h^I_{ijt}|\boldsymbol{x}_{ijt}, h^D_{ijt}] + E[\alpha^B h^B_{ijt}|\boldsymbol{x}_{ijt}, h^D_{ijt}]. \end{aligned}$$

From this equation, one could see that the conditional variance of yield is clearly affected by the individual technology choice. It indicates a case of heteroskedasticity.

To examine the impact of the variance characteristic (α^D) of adopted technology (h^D_{ijt}) on the variability of yields, I adopt the feasible generalized least squares (FGLS) estimation method. Assume the conditional variance of yield has an exponential function form, to guarantee positive values for estimated variances,

$$(39) \qquad Var(y_{ijt}|\boldsymbol{x}_{ijt}, h^D_{ijt}) = exp\{\alpha^N h^N_{ijt} + \alpha^F h^F_{ijt} + \alpha^I h^I_{ijt} + \alpha^B h^B_{ijt} + u_{ijt}\}.$$

Because coefficients from the first-step estimating the production function are consistent, $\hat{e}^2_{ijt}$ is a consistent estimator of e^2_{ijt}. I can estimate the variance function with an ordinary least squares regression as following,

$$(40) \qquad \hat{e}^2_{ijt} = exp\{\alpha^N h^N_{ijt} + \alpha^F h^F_{ijt} + \alpha^I h^I_{ijt} + \alpha^B h^B_{ijt} + u_{ijt}\}$$

$$(41) \qquad \Rightarrow \ log(\hat{e}^2_{ijt}) = \alpha^N h^N_{ijt} + \alpha^F h^F_{ijt} + \alpha^I h^I_{ijt} + \alpha^B h^B_{ijt} + u_{ijt},$$

where $\hat{e}_{ijt}$ is the residual term from the first step estimation and $log(\hat{e}^2_{ijt})$ is calculated. For an easier interpretation of the technology effects, I also estimate an equivalent equation,

$$(42) \qquad log(\hat{e}^2_{ijt}) = \iota^0 + \widetilde{\alpha}^F h^F_{ijt} + \widetilde{\alpha}^I h^I_{ijt} + \widetilde{\alpha}^B h^B_{ijt} + u_{ijt}.$$

The coefficients placed in front of adoption dummy variables, $\widetilde{\alpha}^F$, $\widetilde{\alpha}^I$, $\widetilde{\alpha}^B$, represent the impacts of adopting technologies - fertilizer, intercropping, and both technologies - on the variances of farmers' yields, respectively, in addition to the impact of adopting nothing. One could perceive those impacts as intrinsic characteristics of those technologies. Some technologies lead to a larger variation in the yields, while others reduce that variability.

5.3 Re-Estimate the Farmer's Production

Because of the heteroskedasticity which is demonstrated in the second step, coefficients of the production function acquired through the CRC model in the first step are unbiased and consistent, but inefficient. To correct the heteroskedasticity, I re-estimate the production function with a weight. The weight is the estimated conditional standard deviation of yield, i.e. the square root of the exponential of the fitted value, $\omega_{ijt} = \sqrt{e^{fitted\ value}} = \sqrt{e^{\widehat{log(\hat{e_{ijt}}^2)}}}$. The updated estimators of structural parameters are now unbiased, consistent, and asymptotically efficient.

5.4 Estimate Farmer's Expected Utility

After fully solved the log version of production function, I progress to the underlying structure of farmers' technology adoption decisions.

To estimate the farmer's expected utility function, several additional calculations are required. From the previous three steps, I have derived the conditional expected value and the conditional variance of log of yield through computing the linear predictions after the regression analysis. The specific values are calculated as below. The first groups of equations list the conditional expected values of log of yields under each technology adoption scenario:

$$E[\hat{y^N_{ijt}}|\boldsymbol{x}_{ijt}, h^N_{ijt} = 1] = \hat{\beta^N_t} + \boldsymbol{x}_{ijt}\hat{\boldsymbol{\gamma}} + \hat{\theta_{ij}} \tag{43}$$

$$E[\hat{y^F_{ijt}}|\boldsymbol{x}_{ijt}, h^F_{ijt} = 1] = \hat{\beta^F_t} + \boldsymbol{x}_{ijt}\hat{\boldsymbol{\gamma}} + \hat{\theta_{ij}} + \hat{\theta^F_{ij}} \tag{44}$$

$$E[\hat{y^I_{ijt}}|\boldsymbol{x}_{ijt}, h^I_{ijt} = 1] = \hat{\beta^I_t} + \boldsymbol{x}_{ijt}\hat{\boldsymbol{\gamma}} + \hat{\theta_{ij}} + \hat{\theta^I_{ij}} \tag{45}$$

$$E[\hat{y^B_{ijt}}|\boldsymbol{x}_{ijt}, h^B_{ijt} = 1] = \hat{\beta^B_t} + \boldsymbol{x}_{ijt}\hat{\boldsymbol{\gamma}} + \hat{\theta_{ij}} + \hat{\theta^B_{ij}}. \tag{46}$$

Next groups of equations list the conditional variance of log of yields under each technology adoption scenario:

$$Var[\hat{y^N_{ijt}}|\boldsymbol{x}_{ijt}, h^N_{ijt} = 1] = e^{\widehat{log(\hat{e}^2_{ijt})}} = e^{\hat{a^N}} \tag{47}$$

$$Var[\hat{y^F_{ijt}}|\boldsymbol{x}_{ijt}, h^F_{ijt} = 1] = e^{\widehat{log(\hat{e}^2_{ijt})}} = e^{\hat{a^F}} \tag{48}$$

$$Var[\hat{y^I_{ijt}}|\boldsymbol{x}_{ijt}, h^I_{ijt} = 1] = e^{\widehat{log(\hat{e}^2_{ijt})}} = e^{\hat{a^I}} \tag{49}$$

$$Var[\hat{y^B_{ijt}}|\boldsymbol{x}_{ijt}, h^B_{ijt} = 1] = e^{\widehat{log(\hat{e}^2_{ijt})}} = e^{\hat{a^B}}. \tag{50}$$

The conditional expected values of log of yields vary by both the technology and the farmer-plot, while the conditional variance of log of yields only differ by the technology.

Yet, the variables needed in the expected utility function are the conditional expected value and the conditional variance of yield. With the assumption that the yield follows a lognormal distribution, I translate those values of log of yield to values of yield through the distribution formula. Because $y \sim \mathcal{N}(E[y], Var[y])$ and $Y = e^y$, I have $E(Y) = e^{E[y]+0.5Var[y]}$, and $Var(Y) = [e^{Var[y]} - 1] \times [e^{2E[y]+Var[y]}]$. As a result, for each farmer-plot, I have 4 conditional expected values of yield and 4 conditional variance of yield, corresponding to each technology adoption case.

In addition, recall the farming cost is defined as a summation of the labor cost and the fertilizer cost, $C^D_{ijt} = labor\,cost^D_{ijt} + fertilizer\,cost^D_{ijt}$. All costs are calculated as dollar per acre. The labor costs include both the family labor values and the hired labor values.[10] For each technology, I calculate the average labor costs and fertilizer costs among farmers who adopted that technology in a village (rural) / an enumeration area (urban), and then apply those average costs to all farmers in that specific village/enumeration area. As a result, the farming costs vary by the technology choice, the location, and the farming season. For each farmer-plot, I have 4 estimated farming costs, one for each technology adoption case.

Following the definition of profit as in Equation 2 and given that the farming cost is

[10]The family labor values are computed through multiplying the adjusted total family labor days with the adjusted labor day wage. The adjusted total family labor days are the half of self-reported total family labor days. According to Arthia et al. (2018), at the plot level, the family labor usages reported in the TZNPS through the recall-survey method were about 1.83 times higher than the "true" labor usages, which were collected through weekly visits. The adjusted labor day wage are estimated using the subsistence agricultural worker's day wage and the hired labor's day wage and then devalued by 50% (Deutschmann et al., 2018). The hired labor costs and the fertilizer costs are directly reported in the TZNPS.

a scalar, I obtain the expected value of profit and the variance of profit,

$$\mu_{ijt}^{D} = E[\hat{Y_{ijt}^{D}}|\boldsymbol{x}_{ijt}, h_{ijt}^{D}] - C_{ijt}^{D} \tag{51}$$

$$v_{ijt}^{D} = Var[\hat{Y_{ijt}^{D}}|\boldsymbol{x}_{ijt}, h_{ijt}^{D}]. \tag{52}$$

With these two main variables in hand, I begin to decipher the rationale of farmers' agricultural technology adoption decisions. I use the alternative-specific conditional logit model (ASC logit), aka the McFadden's choice model, to study the factors which influence the farmer's decision-making. In each farming season, farmers face 4 alternative technology choices. Under the assumption that farmers are rational expected utility maximizer, they would choose the technology which gives them the highest expected utility. Employing farmers' actual adoption decisions, I solve the impacts of potential factors.

Starting with a basic model as Equation 1,

$$\max_{h_{ijt}^{N}, h_{ijt}^{F}, h_{ijt}^{I}, h_{ijt}^{B}} EU_{ijt} = m\mu_{ijt} + \rho v_{ijt}, \tag{53}$$

where the expected value of profits and the variance of profits for each technology adoption scenario are the alternative-specific variables, and the year fixed effect is the case-specific variable, i.e. farmer-plot-specific variable. I derive farmers' responses to the profit value (m) and the variance of profit (ρ), both the magnitude and the direction.

Furthermore, since existing works have offered different explanations for farmers' adoption decisions, I enhance my basic decision-making model. I include 4 additional groups of potential influencing factors, which have been shown in the literature,

$$\max_{h_{ijt}^{N}, h_{ijt}^{F}, h_{ijt}^{I}, h_{ijt}^{B}} EU_{ijt} = m\mu_{ijt} + \rho v_{ijt} + \boldsymbol{\phi^{T} Z_{ijt}^{T}} + \boldsymbol{\phi^{L} Z_{ijt}^{L}} + \boldsymbol{\phi^{M} Z_{ijt}^{M}} + \boldsymbol{\phi^{C} Z_{ijt}^{C}}, \tag{54}$$

where $\boldsymbol{Z_{ijt}^{T}}$ represents a group of distance variables which aim to capture the potential difficulty of traveling to the market, $\boldsymbol{Z_{ijt}^{L}}$ represents a group of family composition variables which aim to capture the potential labor constraint, $\boldsymbol{Z_{ijt}^{M}}$ represents a group of family financial situation variables which aim to capture the potential credit constraint, and $\boldsymbol{Z_{ijt}^{C}}$ represents a group of crop choice variables. Using this more comprehensive model, I acquire more precise estimates for the two core factors, the monetary attraction (m) and the risk aversion (ρ).

Lastly, to demonstrate the importance of a farmer's risk aversion in the decision-making process, I estimate a model commonly used in the literature which only considers about the mean of return,

$$\max_{h^N_{ijt},h^F_{ijt},h^I_{ijt},h^B_{ijt}} EU_{ijt} = m\mu_{ijt} + \boldsymbol{\phi^T Z^T_{ijt}} + \boldsymbol{\phi^L Z^L_{ijt}} + \boldsymbol{\phi^M Z^M_{ijt}} + \boldsymbol{\phi^C Z^C_{ijt}}, \tag{55}$$

and compare it to my enhanced model, Equation 54, using the likelihood-ratio test.

6 Empirical Results

Analogous to the empirical strategy, empirical results are presented in 4 sub-sections: estimates of farmers' yields, estimates of the variability of farmers' yields, adjusted estimates of farmers' yields, and the influences of various factors on farmers' decisions of technology adoptions.

6.1 Farmer's Yield

In this first subsection, I present the estimations of the farmer's production function.

Estimating the parameters of CRC model as explained in Section 5.1, I include the following exogenous control variables: household location (rural/urban), household head's gender (male/not), household size, household member composition [the number of girls (age $<$ 12 years), the number of boys (age $<$ 12 years), the number of women (age 12-60), and the number of men (age 12-60)], average annual temperature, average precipitation amount of the last 12 months, plot size, soil quality, plot slope, and plot fallowing history (ever yes/no). The derived structural parameters and standard errors are shown in Table 5.

The relevant parameters are coefficients placed in front of technology adoption dummies. Revisiting Equation 15, I obtain the expected returns to technology adoptions which are $\tilde{\beta}^D + \theta^D_{ij}$, where $\tilde{\beta}^D$ is the average (additional) benefit of adopting technology D, and θ^D_{ij} is the farmer-plot-specific (additional) returns to adopting technology D. The technology-specific productivity, θ^D_{ij}, are predicted using projections of farmers' adoption histories, as in Equation 17 - 20. Given a two-year panel dataset, there are four possible adoption profiles for each technology: 1) never-adopter, someone who has not adopted the technology in any year; 2) dis-adopter, someone who has adopted the technology in year 1, but not adopted it in year 2; 3) late-adopter, someone who has not adopted the technology in year 1, but adopted it in year 2; and 4) always-adopter, someone who has adopted the technology in both years. Therefore, I derive 4 values of heterogeneous returns for each technology adoption.

In Figure 1, I graph the returns to adopting only fertilizer, adopting only intercropping, and adopting both technologies; separated bars indicate each farmer adoption profile. Since this research aims to examine the rationale of adoption and non-adoption, not farmers' technology switching behaviors, Figure 1 only shows the expected returns for the never-adopter and the always-adopter. Estimations of the other two groups are presented as secondary results, in the appendix Figure C.1.

Based on Figure 1, the estimated returns to adopting only fertilizer and adopting both technologies are significantly positive for always-adopters, and are not statistically different from zero for never-adopters. The returns of always-adopters are much higher than them of never-adopters for those two technology sets. The specific coefficient for always-adopters of adopting only fertilizer is 0.83, which means that the yield is 126.4% higher when the always-adopter adopts it comparing to he/she does not adopt it.[11] The specific coefficient for always-adopters of adopting both technologies is 0.52, which indicates that the yield is 66.6% higher when the always-adopter adopts both fertilizer and intercropping comparing to he/she does not adopt those two technologies. Considering those technologies offer a 126% increase or a 67% increase in yield, respectively, these sizable expansions in yield could be understood as a reason for adoption. Furthermore, the return coefficients to adopting both technologies are -1.24 for never-adopters and 0.52 for always-adopters. These values do not equal to the summation of return coefficients to only fertilizer and return coefficients to only intercropping. This pattern indicates that the combination of two technologies produces a different technology altogether. Lastly, for both never-adopters and always-adopters, the

[11] The percentage is calculated using the formula, $100 \times [e^{(\omega - \frac{1}{2}Var(\omega))} - 1]$, where ω is the coefficient.

return coefficients to adopting only intercropping are approximately zero. If the rationale for adoptions derives only from the expected returns, no farmers would ever adopt it. To the contrary, in each season, about 44% of plots are intercropped. Because each technology has multiple attributes, such as characteristics which affect the mean of yield, and characteristics which influence the variance of yield, the rationale for adoptions could be multidimensional, too.

6.2 Variability of Farmer's Yield

After solving the structural parameters, I examine the impact of technologies on the variability of farmers' yields. Results are shown in Table 5. Adopting only intercropping significantly decreases the conditional variance of log of yield by 13.1%, compared with using no technology. Adopting only fertilizer increase the conditional variance of log of yield by 15.8%. The impacts of those two adoptions are significantly different from each other. Adopting both intercropping and fertilizer together shows a sign of reducing the conditional variance, while the result is not statistically significant.

These findings offer two theories for farmers' adoption decisions. Firstly, farmers may adopt only intercropping to achieve the benefit of reductions in revenue variance. Secondly, even though the expected returns to adopting only fertilizer are considerable, the attendant risks are even larger. If farmers are risk-averse, they may choose to not adopt those technologies, as sacrificing the benefit of increasing expected returns to avoid carrying the costs of fluctuations in revenues. Moreover, similar to the expected returns, the variance characteristic of adopting both technologies presents itself as a unique technology, rather than a simple aggregation of two technologies.

6.3 Adjusted Farmer's Yield

Due to the heteroskedasticity in the production function, I re-estimate the CRC model with a weight. The weights are specific to the technology, the same as the variance characteristics.

Adjusted estimates of structural parameters are similar to coefficients obtained in the first step. Results are listed in column "Third-Stage" of Table 4. Looking at Figure 2, one can see that the patterns for returns to technology adoptions stay the same as before. The returns to adopting only fertilizer and adopting both technologies are significantly positive for always-adopters, while the returns to adopting only intercropping are always around zero.

6.4 Farmers' Expected Utility

Using the estimations from the previous three steps and the lognormal distribution formula, I obtain the conditional expected value and conditional variance of both log of yield and yield, as shown in Table D.1. On average, adopting only fertilizer provides the largest conditional expected value of yield, and the conditional expected values of yield for adopting only intercropping and adopting neither technology are similar. For the conditional variance of log of yield, adopting only intercropping represents the lowest variance, and adopting only fertilizer leads to the highest variance.

Table 6 shows the farming costs for each technology adoption case. Adopting only intercropping requires the least spending, around \$27; while adopting only fertilizer uses the most spending, around \$63.

Table 7 presents farmers' expected values of profit and variances of profit. On average, farmers' expectations of profits are approximately \$79/acre for adopting neither technology, \$86/acre for adopting only fertilizer, \$85/acre for adopting only intercropping, and \$27/acre for adopting both technology; while the variances of profits are \$6159/acre, \$12627/acre, \$5001/acre, and \$3169/acre, respectively in the same order.[12]

[12] Adopting both technologies has the lowest average numbers for both those variables because some farmers, i.e. never-adopters, experience negative conditional expected values of log of yield. This scenario lowers the mean of conditional expected values of yield, and also affects both the mean and the variance of yield with larger magnitudes after the log-normal translation.

6.5 Farmers' Technology Adoption Decisions

Bringing the farmers' expected values of profit and variances of profit into the expected utility function, I examine their influences on farmer's technology adoption decisions through both the basic model, Equation 53, and the enhanced model, Equation 54. The additional case-specific variables included in the enhance model are 1) distance between home and plot (km), distance between home and market (km), 2) household member composition [the number of children (age $<$ 12 years), the number of women (age 12-60), and the number of men (age 12-60)], 3) household's total asset values ($1000), salary as household's main source of cash income, business revenue as household's main source of cash income, remittance as household's main source of cash income, 4) growing maize as the main crop, growing rice as the main crop, growing cassava as the main crop, the average annual temperature, and the average precipitation amount of the last 12 months.

The alternative-specific conditional logit model results are shown in Table 8. In both the basic model and the enhanced model, the expected value of profit has a significant positive effect on farmer's expected utility, while the variance of profit has a significant negative positive effect on farmer's expected utility. The empirical results are consistent with my hypothesis. Farmers' technology adoption choices are notably impacted by both the mean and variance of profits. Specifically, farmers are profit lover ($m > 0$) and risk averse ($\rho < 0$).

The raw coefficients of the ASC logit model show the effect of 1-unit change in the independent variable on the log odds of the dependent variable equaling 1. For a better interpretation of the influences, I calculate the marginal effects at the means of the independent variables using the enhanced specification, shown in Table 9. The marginal effects demonstrate a clear pattern of how farmers respond to the expected profit and the risk associated with the profit. For each technology, an increase in its own expected profit would raise the probability of it being adopted, and an increase in the expected profit of other technologies would drop the probability of it being adopted. For example, for 1 dollar increase in the expected profit of adopting only fertilizer, it increases the probability that farmers adopt it by 0.0026 percentage points, while for 1 dollar increase in the expected profit of adopting only intercropping, it decreases the probability that farmers adopt only fertilizer by 0.0014 percentage points.

The effect of variance is exactly opposite. For each technology, an increase in its own profit variance would decreases the probability of it being adopted, and an increase in the profit variance of other technologies would raise the probability of it being adopted. Because the variance of profits usually spreads out, I choose to compute the marginal effect using $1000-unit. As shown in Table 9, for 1000 dollar increase in the profit variance of adopting only fertilizer, it decreases the probability that farmers adopt it by 0.0057 percentage points, while for 1000 dollar increase in the profit variance of adopting only intercropping, it increases the probability that farmers adopt only fertilizer by 0.0030 percentage points.

Those marginal effects may look small, but both the expected value of profit and the variance of profit play vital roles in farmer's decision making process. I predict the probabilities of choosing each technology using the the enhanced specification, shown in Table 10. If I estimate the probabilities at the means of the expected value of profit and at the means of the variance of profit, the probability of adopting only fertilizer is 0.043 and the probability of adopting only intercropping is 0.506. On the other hand, if I calculate the probabilities at the means of the expected value of profit and set the variance of profit to be zero, the probability of adopting only fertilizer dramatically increases to 0.106 since the risk is eliminated, while the probability of adopting only intercropping drops to 0.438, as the benefit is taking away.

In addition, to emphasize the importance of farmers' risk aversion, I compare the model used in the literature, Equation 55, and my enhanced model, Equation 54. The χ^2 statistic of the likelihood-ratio test is 213.05, with a probability 0.000. The result shows that by adding in the consideration of the variance of profit, the farmer's decision-making model is significantly improved.

7 Robustness Checks

To address the concern that farmers may adopt certain agricultural technologies according to the crops they grow, I conduct following analysis.

First of all, I examine the technology adoptions across various crops. Focusing on crops that have grown on at least 3% of total plots over either farming season, this criteria limits to 9 crops - maize, rice, beans, groundnuts, sorghum, sweet potatoes, cow pea, pigeons pea, and sunflower. The adoption rates of technologies over those 9 crops are shown in D.2. All four technologies have been used with those crops. There is no special selection of technology due to the crop choice.

In addition, I restrict the analysis sample to plots that have grown at least one of the three most common crops - maize, rice, and beans, and repeat all 4 steps of empirical estimations. The distribution of returns to adoptions are displayed in Figure 3 and Figure 4. For adopting only fertilizer and adopting both technologies, always-adopters enjoy significantly positive returns, while adopting only intercropping does not generate additional returns. The effects of adopting technologies on the variability of yields are shown in Table 11. Similar as results from the full sample, adopting only intercropping and adopting both technologies reduce the variance of yields, while adopting only fertilizer increases the variance. Yet, due to a smaller sample size, results are not statistical significant. The impacts of the expected value of profit and the variance of profit on farmer's decisions are presented in Table 12 and Table 13. Farmers respond to the expected value of profit positively and the variance of profit negatively. If removing the production risk associated with fertilizer, the probability of adopting only fertilizer increases from 0.057 to 0.074. Empirical results are reassuring, as estimations using the sub-sample show the same patterns with the estimations using the full sample.

8 Conclusion

Within the literature about agricultural technology adoption, numerous works have been conducted to examine and explain the low and unstable adoption rates in Sub-Saharan Africa. The majority of studies have focused on the obstacles that caused these insufficient usages, and believed that adoption rates should be and could be boosted after some reforms. This research offers an alternative opinion that both the technology adoption and non-adoption decisions could be optimal, due to the heterogeneities in farmers and in technologies. Since farmers have different productivities in farming, they enjoy different returns to agricultural technology adoptions. In addition, because farmers care about both the expectation and the risk, the analysis of farmers' choices should consider multiple moments of the profit distribution.

To understand the rationale behind farmers' decisions about agricultural technology adoption, I construct a farmer's decision-making model which explicitly takes into account both the expected value and the variance of a farmer's profits. Within the expected utility function, I build the farmer's production function which allows heterogeneous returns, selection bias, and heterogeneous variances in the technology adoption.

Using the Tanzania Living Standards Measurement Study (LSMS) panel dataset and four technology choices, I estimate my farmer's decision-making model. With a completed empirical estimation, I have the expected returns of each technology for each group of farmers, the variance effects of each technology, the farmers' response to profit expectations, and the farmers' risk aversion level.

In general, adopting only fertilizer raises both the expected return of revenue and the variance of revenue; adopting only intercropping does not change the expected return of revenue, but reduces the variance of revenue significantly; and adopting both technologies increases the expected return of revenue for subgroup of farmers while at the same time causes variations in the revenue. Which technology to adopt depends on farmers' technology-specific productivities, their response to the expected profit, which is shown to be positive as farmers are money lover, and their response to the variance of profit, which is shown to be negative as farmers are risk averse.

Unraveling the farmer's decision-making model, the rationales behind farmers' decisions about agricultural technology adoption are been presented. These empirical outcomes can explain the low adoption rates of an intensively promoted higher-average-return technology such as fertilizer, and justify the high adoption rates of a seemingly unprofitable technology such as intercropping. Future policy suggestions, for either technology promotions or dis-promotions, should take into account of the individual idiosyncrasy, the distribution of technology returns, and full aspects of farmers' concerns, i.e. both the expected value and the variance of profits.

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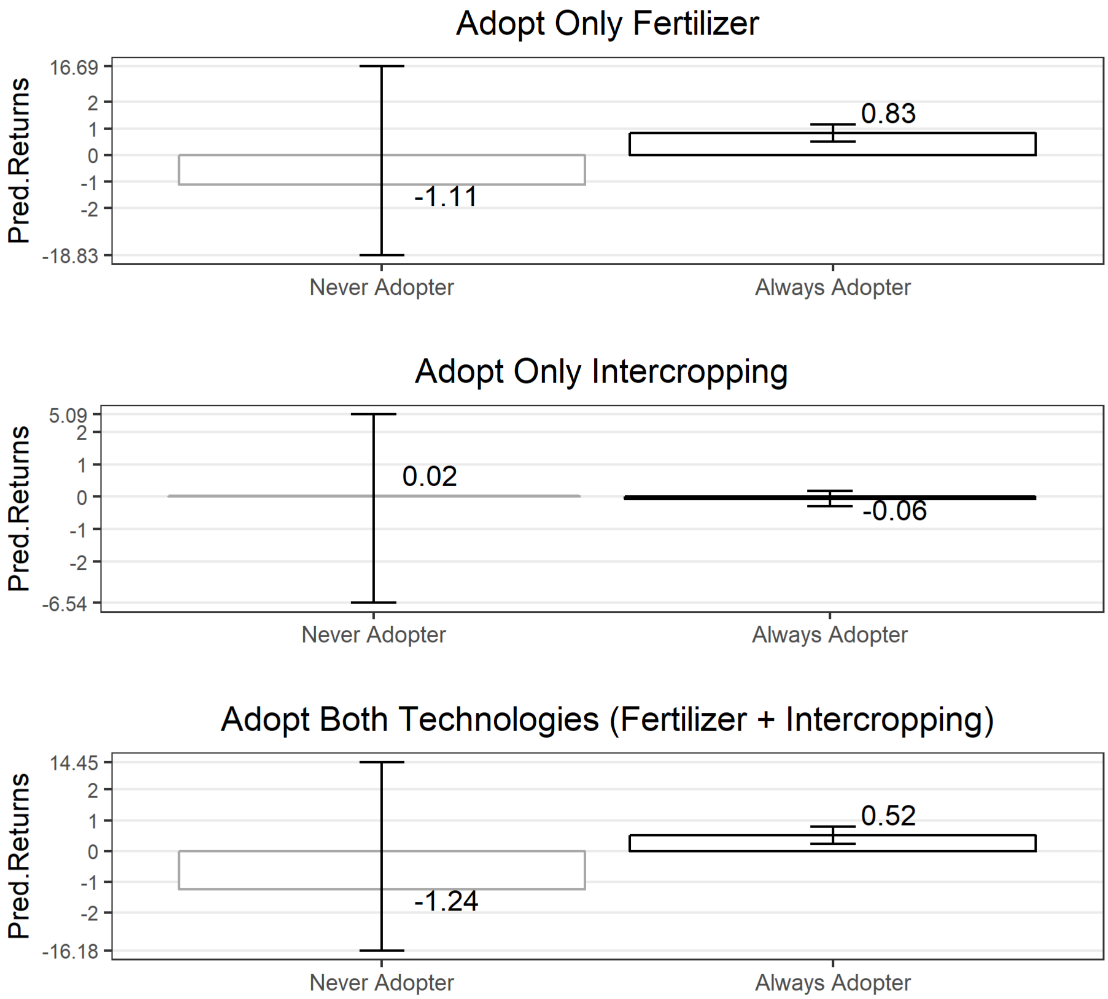
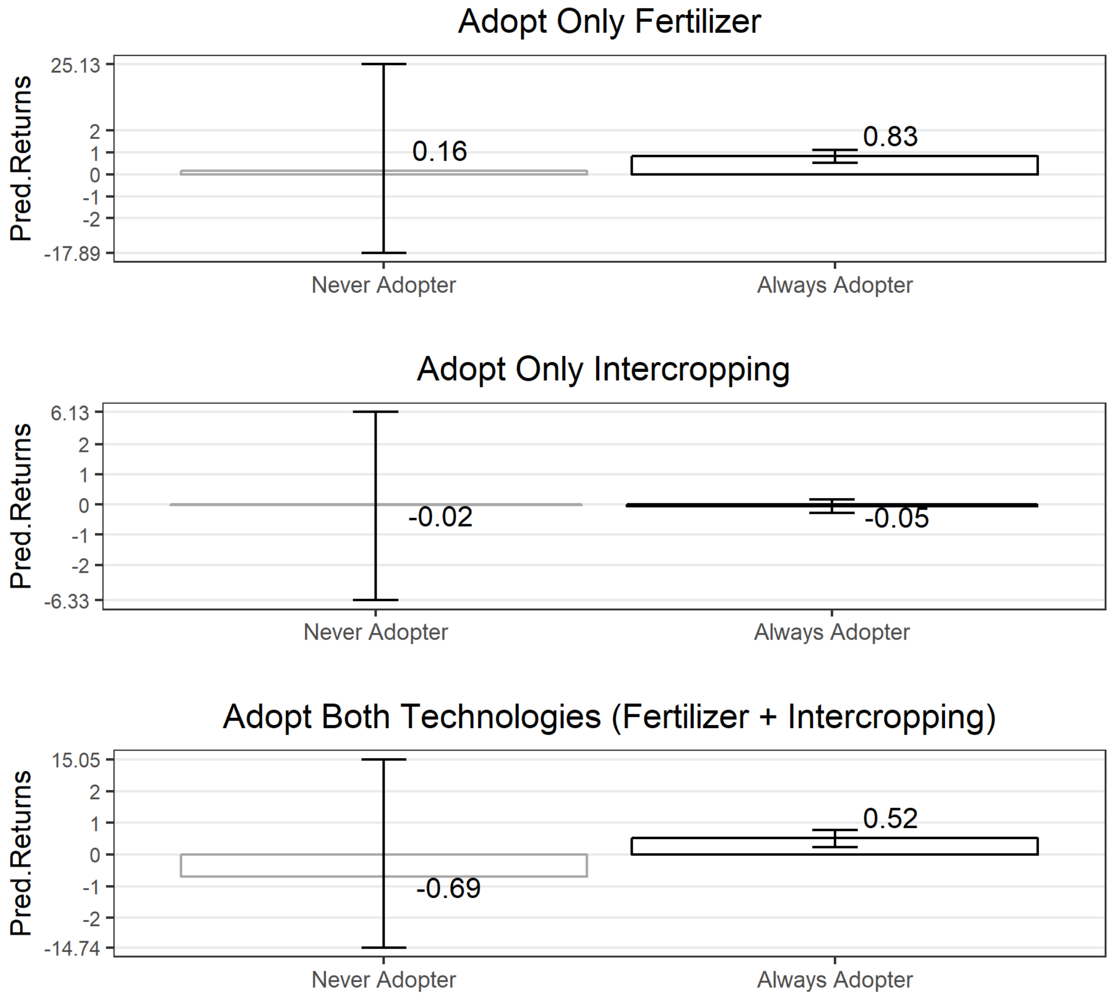
Figures

Figure 1: Distribution of Predicted Returns to Adoptions (Full Sample)



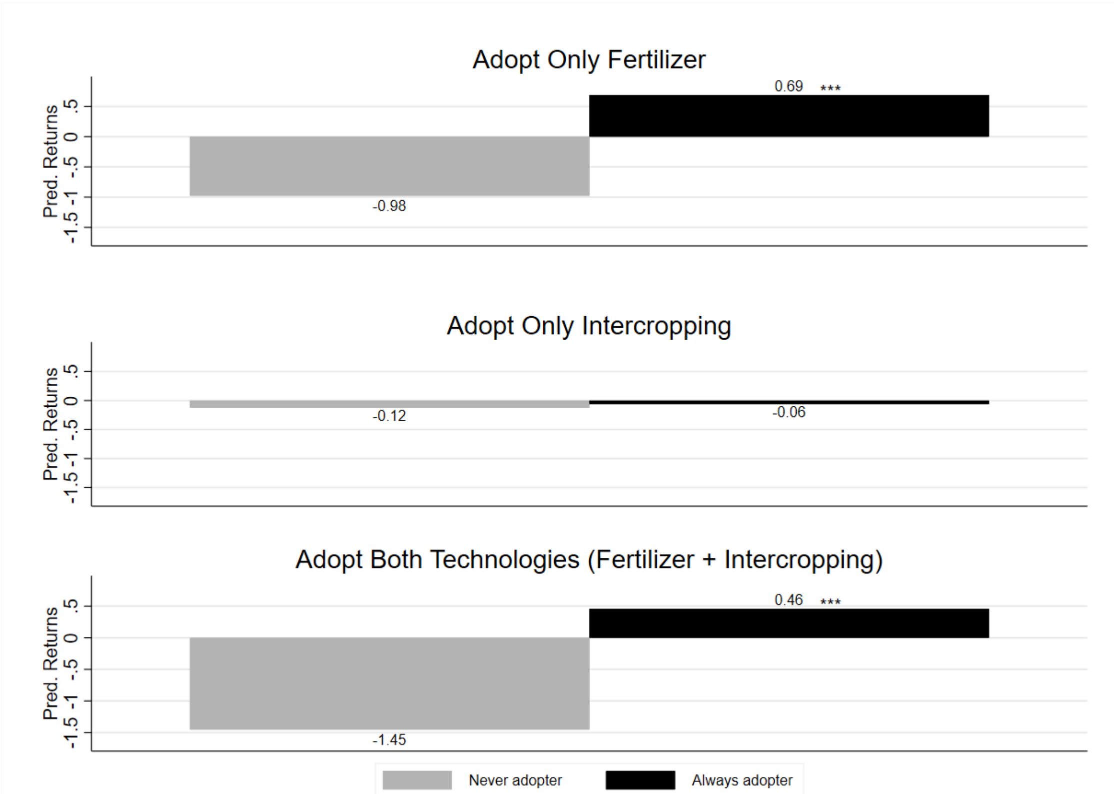
Note: This figure is created using all plots from the analysis sample. Never adopter refers to farmer who adopted the technology in neither farming season; always adopters refers to farmer who adopted the technology in both farming seasons. The boxes represent predicted returns, which are calculated as $\beta + \theta$. The bars represent the 95% confidence levels, which are calculated through bootstrapping 3075 iterations.

Figure 2: Distribution of Predicted Weighted Returns to Adoptions (Full Sample)



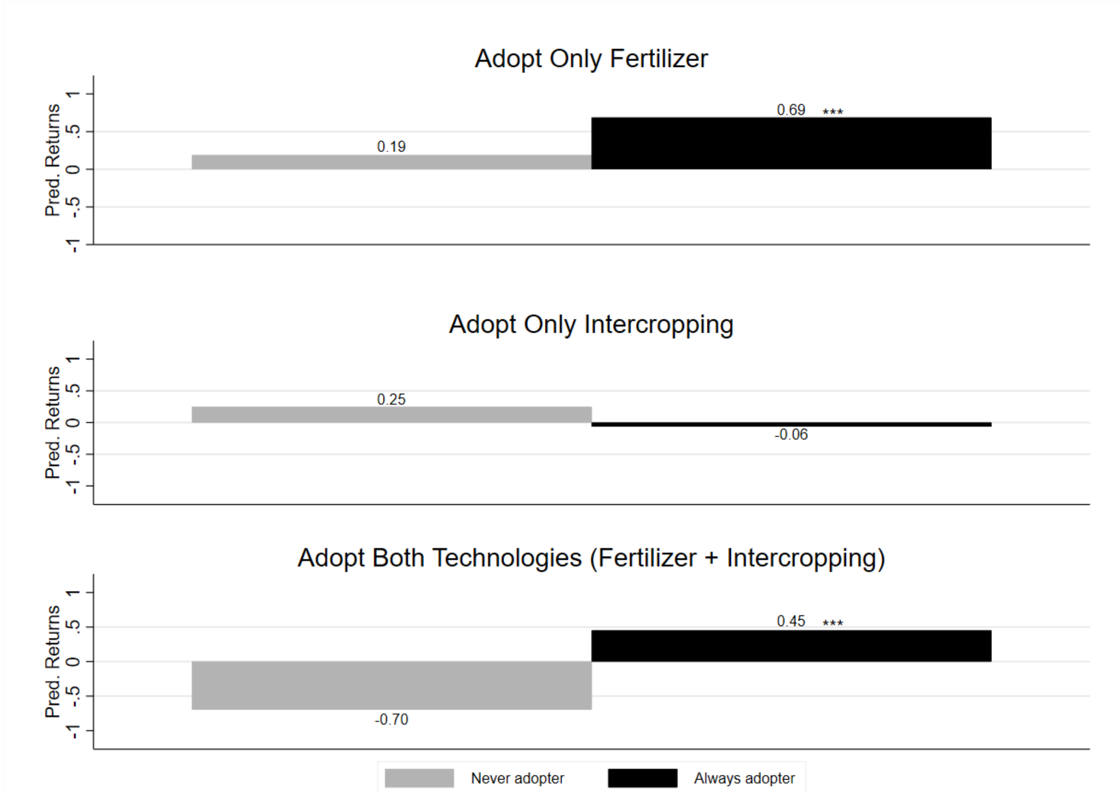
Note: This figure is created using all plots from the analysis sample. Never adopter refers to farmer who adopted the technology in neither farming season; always adopters refers to farmer who adopted the technology in both farming seasons. The boxes represent predicted returns, which are calculated as $\beta + \theta$. The bars represent the 95% confidence levels, which are calculated through bootstrapping 3050 iterations.

Figure 3: Distribution of Predicted Returns to Adoptions (Sub-Sample)



Note: This figure is created using plots which have grown at least one of the three most common crops (maize, paddy, beans) in both farming seasons from the analysis sample. Never adopter refers to farmer who adopted the technology in neither farming season; always adopters refers to farmer who adopted the technology in both farming seasons. The boxes represent predicted returns, which are calculated as $\beta + \theta$.

Figure 4: Distribution of Predicted Weighted Returns to Adoptions (Sub-Sample)



Note: This figure is created using plots which have grown at least one of the three most common crops (maize, paddy, beans) in both farming seasons from the analysis sample. Never adopter refers to farmer who adopted the technology in neither farming season; always adopters refers to farmer who adopted the technology in both farming seasons. The boxes represent predicted returns, which are calculated as $\beta + \theta$.

Tables

Table 1: Descriptive Statistics (Household Level) - Household Characteristics

Household Level	2010-2011		2012-2013	
Variables	Mean	S.D.	Mean	S.D.
Household is at rural	0.87	0.34	0.86	0.35
Household head is male	0.77	0.42	0.76	0.43
Household head works in agriculture	0.84	0.36	0.85	0.36
Household size	5.84	3.30	5.76	3.30
Number of female children (age < 12)	1.10	1.22	1.05	1.20
Number of male children (age < 12)	1.05	1.16	1.02	1.17
Number of female active members	1.68	1.20	1.65	1.18
Number of male active members	1.64	1.32	1.64	1.29
Number of female elder members (age > 60)	0.21	0.43	0.22	0.43
Number of male elder members (age > 60)	0.17	0.39	0.17	0.39
Average annual temperature ($°C$)	22.60	2.59	22.61	2.58
Average rainfall in the past 12 month (mm)	800.14	215.78	802.99	215.27
Number of households	1628		1628	

Note: The descriptive statistics are created using the analysis sample.

Table 2: Descriptive Statistics (Plot Level) - Plot Characteristics

Plot Level	2010-2011		2012-2013	
Variables	Mean	S.D.	Mean	S.D.
Plot quality and inputs				
Plot area (acre)	2.67	5.78	2.93	6.40
Plot soil quality	2.41	0.61	2.43	0.60
Plot slope steepness	1.37	0.55	1.33	0.53
Plot has fallowed ever	0.06	0.23	0.02	0.16
Household could sell the plot	0.74	0.44	0.78	0.41
Pesticide usage ($)	0.83	11.95	0.77	5.31
Family labor usage (days per acre)				
land prep. and planting	23.33	35.49	24.71	34.81
weeding	21.80	32.55	23.08	33.63
harvesting	17.07	29.51	15.79	25.67
total	62.53	84.30	66.48	89.15
Hired workers usage (dollar per acre)				
land prep. and planting	1.96	8.27	2.82	11.21
weeding	1.70	6.72	2.57	14.06
harvesting	1.14	4.99	2.05	10.04
total	4.87	16.10	7.65	28.75
Harvest value (dollar per acre)				
value	106.91	505.55	142.68	318.48
Number of plots	2523		2523	

Note: The descriptive statistics are created using the analysis sample.

Table 3: Descriptive Statistics (Plot Level) - Adoptions of Agricultural Technologies

(number of plots)	Adoption in 2012-2013				
Adoption in 2010-2011	<1> Neither	<2> Fertilizer	<3> Intercropping	<4> Both	Total
<1> Adopted neither technology	557	61	358	21	997
<2> Adopted only fertilizer	44	82	20	51	197
<3> Adopted only intercropping	319	22	729	43	1113
<4> Adopted both technologies	28	36	44	108	216
Total	948	201	1151	223	2523

(percentage of plots)	Adoption in 2012-2013				
Adoption in 2010-2011	<1> Neither	<2> Fertilizer	<3> Intercropping	<4> Both	Total
<1> Adopted neither technology	22.08%	2.42%	14.19%	0.83%	39.52%
<2> Adopted only fertilizer	1.74%	3.25%	0.79%	2.02%	7.81%
<3> Adopted only intercropping	12.64%	0.87%	28.89%	1.70%	44.11%
<4> Adopted both technologies	1.11%	1.43%	1.74%	4.28%	8.56%
Total	37.57%	7.97%	45.62%	8.84%	100.0%

Note: The descriptive statistics are created using the analysis sample.

Table 4: Heterogeneous Return to Technology Adoption: CRC Model OMD Structural Estimates (Full-Sample)

	First-Stage	Third-Stage		First-Stage	Third-Stage		First-Stage	Third-Stage		First-Stage	Third-Stage
$\lambda_0^F =$	-0.218	-0.060	$\lambda_0^I =$	0.012	-0.016	$\lambda_0^B =$	-0.239	-0.168	$\lambda_0^N =$	-0.029	-0.030
	(1.657)	(1.327)		(2.845)	(3.565)		(1.339)	(1.255)		(0.058)	(0.057)
$\lambda_1^F =$	1.563	0.296	$\lambda_1^I =$	-0.021	0.022	$\lambda_1^B =$	1.813	1.264	$\lambda_1^N =$	-0.076	-0.073
	(13.911)	(10.997)		(4.684)	(5.774)		(10.349)	(9.927)		(0.109)	(0.109)
$\lambda_2^F =$	1.784	0.521	$\lambda_2^I =$	0.086	0.134	$\lambda_2^B =$	1.898	1.353	$\lambda_2^N =$	-0.007	-0.006
	(13.916)	(11.000)		(4.684)	(5.773)		(10.356)	(9.928)		(0.112)	(0.110)
$\lambda_3^F =$	-1.411	-0.144	$\lambda_3^I =$	-0.147	-0.189	$\lambda_3^B =$	-1.952	-1.403	$\lambda_3^N =$	0.277	0.278
	(13.916)	(11.001)		(4.686)	(5.776)		(10.351)	(9.927)		(0.121)	(0.120)
$\tilde{\beta}^F =$	-0.888	0.218	$\tilde{\beta}^I =$	0.012	-0.005	$\tilde{\beta}^B =$	-1.000	-0.527			
	(12.264)	(9.680)		(1.840)	(2.213)		(9.027)	(8.695)			

Note: The analysis uses all plots from the analysis sample. Standard errors are calculated using the bootstrapping method and reported in parentheses. In the first stage, the bootstrap conducts 3075 iterations; in the third stage, the bootstrap conducts 3050 iterations. OMD is optimal weighted minimum distance, where the weight matrix is the inverted reduced form variance-covariance matrix. Specifications in both stages include exogenous covariates: household location (rural/urban), household head's gender (male/not), household size, household member composition [the number of girls (age $<$ 12 years), the number of boys (age $<$ 12 years), the number of women (age 12-60), and the number of men (age 12-60)], average annual temperature, average precipitation amount of the last 12 months, plot size, soil quality, plot slope, and plot fallowing history (ever yes/no).

Table 5: Variability of Farmer's Yield (Full-Sample)

	Ln of Conditional Variance of Ln of Yield $log\{Var(y_{ijt}\|\boldsymbol{x_{ijt}}, h_{ijt}^D)\}$
Adopt only fertilizer	0.158
	(0.137)
Adopt only intercropping	-0.131*
	(0.073)
Adopt both technologies	-0.110
	(0.123)
N	5046
R^2	0.002
Intercropping = Fertilizer ($P - Value$)	0.031
Fertilizer = Both Tech. ($P - Value$)	0.090

Note: The analysis uses all plots from the analysis sample. The dependent variable is the natural logarithm of conditional variance of the natural logarithm of yield. It is estimated as the natural logarithm of the square of the residual term of the first stage production function estimation. Standard errors are clustered at the cluster level, i.e the enumeration area for the urban areas and the village for the rural areas, and reported in parentheses.

Table 6: Descriptive Statistics - Farming Costs

Cost	N	Mean Labor	Mean Fertilizer	Mean Total
Adopt neither technology	5046	35.81	0.00	35.81
Adopt only fertilizer	5046	44.61	18.04	62.65
Adopt only intercropping	5046	27.22	0.00	27.22
Adopt both technologies	5046	31.46	15.92	47.38

Note: The descriptive statistics are created using the analysis sample. Farming costs are varied by technolgies and villages. Labor costs are the total costs of both family labors and hired labors.

Table 7: Descriptive Statistics - Expected Value of Profit and Variance of Profit

Profit	N	Mean	S.D.
Expected value			
Adopt neither technology	5046	79.09	55.38
Adopt only fertilizer	5046	85.77	78.32
Adopt only intercropping	5046	84.67	53.43
Adopt both technologies	5046	27.47	62.59
Variance			
Adopt neither technology	5046	6158.58	9418.00
Adopt only fertilizer	5046	12627.42	18361.06
Adopt only intercropping	5046	5001.87	7493.69
Adopt both technologies	5046	3169.33	7373.44

Note: The descriptive statistics are created using the analysis sample. Profits are calculated as farming revenus minus farming cost.

Table 8: Alternative-Specific Conditional Logit Model: the Impacts of the Expectated Value of Profit and the Variance of Profit (Full-Sample)

	(1) Basic Eq. (53)	(2) Enhanced Eq. (54)	(3) Mean-Only Eq. (55)
Expected value of profit	0.059***	0.063***	0.039***
(\$/acre)	(0.002)	(0.002)	(0.001)
Variance of profit	-0.119***	-0.138***	
(\$1000/acre)	(0.007)	(0.008)	
Alternative-Specific Variables	Y	Y	Y
Case-Specific Variables	N	Y	Y
Year Fixed Effect	Y	Y	Y
N	20184	20184	20184
Case	5046	5046	5046
Likelihood-ratio test between (2) and (3): Probability $> \chi^2 = 0.000$.			

Note: The analysis uses all plots from the analysis sample. Standard errors are reported in parentheses. Case-specific variables in specifications (2) and (3) are the distance between home and plot (km), the distance between home and market (km), household member composition [the number of children (age $<$ 12 years), the number of women (age 12-60), and the number of men (age 12-60)], average annual temperature, average precipitation amount of the last 12 months, household's asset values (\$1000), salary as household's main source of cash income (yes/no), business revenues as household's main source of cash income (yes/no), remittance as household's main source of cash income (yes/no), growing maize as the main crop (yes/no), growing rice as the main crop (yes/no), and growing cassava as the main crop (yes/no).

Table 9: Alternative-Specific Conditional Logit Model: the Marginal Effects of the Expectated Value of Profit and the Variance of Profit (Full-Sample)

	Probability of ...			
Variable	Adopt neither tech.	Adopt only fertilizer	Adopt only intercrop.	Adopt both tech.
Expected value of profit (\$/acre) of ...				
Adopt neither technology	0.0155	-0.0012	-0.0141	-0.0001
	(0.000)	(0.000)	(0.000)	(0.000)
Adopt only fertilizer	-0.0012	0.0026	-0.0014	-0.0000
	(0.000)	(0.000)	(0.000)	(0.000)
Adopt only intercropping	-0.0141	-0.0014	0.0156	-0.0001
	(0.000)	(0.000)	(0.000)	(0.000)
Adopt both technologies	-0.0001	-0.0000	-0.0001	0.0003
	(0.000)	(0.000)	(0.000)	(0.000)
Variance of profit (\$1000/acre) of ...				
Adopt neither technology	-0.0340	0.0026	0.0311	0.0003
	(0.000)	(0.000)	(0.000)	(0.000)
Adopt only fertilizer	0.0026	-0.0057	0.0030	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)
Adopt only intercropping	0.0311	0.0030	-0.0344	0.0003
	(0.000)	(0.000)	(0.000)	(0.000)
Adopt both technologies	0.0003	0.0000	0.0003	-0.0006
	(0.000)	(0.000)	(0.000)	(0.000)
Predicted probability	44.607%	4.296%	50.644%	0.450%

Note: The analysis uses all plots from the analysis sample. *P-values* are reported in parentheses. The marginal effects are estimated following the Enhanced specification, column (2) of Table 9. They are calculated at the means of the independent variables by using the estimation sample.

Table 10: Alternative-Specific Conditional Logit Model: Predicted Probability of Adoption (Full-Sample)

Model	(1) from actual model	(2) if set variance to 0
Adopt neither technology	0.446	0.453
Adopt only fertilizer	0.043	0.106
Adopt only intercropping	0.506	0.438
Adopt both technologies	0.005	0.003

Note: The analysis uses all plots from the analysis sample. The predicted probabilities of choosing each alternative (technology) are estimated following the Enhanced specification, column (2) of Table 9. Only one alternative per case can be chosen. In specification (1), the probabilities are calculated at the means of the expected value of profit and the variance of profit. In specification (2), the probabilities are calculated at the means of the expected value of profit and set the variance of profit to be zero.

Table 11: Variability of Farmer's Yield (Sub-Sample)

	Ln of Conditional Variance of Ln of Yield $log\{Var(y_{ijt}\|\boldsymbol{x_{ijt}}, h^D_{ijt})\}$
Adopt only fertilizer	0.116
	(0.146)
Adopt only intercropping	-0.104
	(0.083)
Adopt both technologies	-0.017
	(0.125)
N	3862
R^2	0.001
Intercropping = Fertilizer ($P-Value$)	0.128
Fertilizer = Both Tech. ($P-Value$)	0.433

Note: The analysis uses plots which have grown at least one of the three most common crops (maize, rice, beans) in both farming seasons from the analysis sample. The dependent variable is the natural logarithm of conditional variance of the natural logarithm of yield. It is estimated as the natural logarithm of the square of the residual term of the first stage production function estimation. Standard errors are clustered at the cluster level, i.e the enumeration area for the urban areas and the village for the rural areas, and reported in parentheses.

Table 12: Alternative-Specific Conditional Logit Model: the Impacts of the Expectated Value of Profit and the Variance of Profit (Sub-Sample)

	(1) Basic Eq. (53)	(2) Enhanced Eq. (54)	(3) Mean-Only Eq. (55)
Expected value of profit	0.018***	0.026***	0.019***
($/acre)	(0.001)	(0.002)	(0.001)
Variance of profit	-0.018**	-0.048***	
($1000/acre)	(0.009)	(0.009)	
Alternative-Specific Variables	Y	Y	Y
Case-Specific Variables	N	Y	Y
Year Fixed Effect	Y	Y	Y
N	15448	15448	15448
Case	3862	3862	3862
Likelihood-ratio test between (2) and (3): Probability $> \chi^2 = 0.000$.			

Note: The analysis uses plots which have grown at least one of the three most common crops (maize, rice, beans) in both farming seasons from the analysis sample. Standard errors are reported in parentheses. Case-specific variables in specifications (2) and (3) are the distance between home and plot (km), the distance between home and market (km), household member composition [the number of children (age $<$ 12 years), the number of women (age 12-60), and the number of men (age 12-60)], average annual temperature, average precipitation amount of the last 12 months, household's asset values ($1000), salary as household's main source of cash income (yes/no), business revenues as household's main source of cash income (yes/no), remittance as household's main source of cash income (yes/no), growing maize as the main crop (yes/no), growing rice as the main crop (yes/no), and growing cassava as the main crop (yes/no).

Table 13: Alternative-Specific Conditional Logit Model: Predicted Probability of Adoption (Sub-Sample)

Model	(1) from actual model	(2) if set variance to 0
Adopt neither technology	0.408	0.396
Adopt only fertilizer	0.057	0.074
Adopt only intercropping	0.481	0.485
Adopt both technologies	0.054	0.045

Note: The analysis uses plots which have grown at least one of the three most common crops (maize, rice, beans) in both farming seasons from the analysis sample. The predicted probabilities of choosing each alternative (technology) are estimated following the Enhanced specification, column (2) of Table 13. Only one alternative per case can be chosen. In specification (1), the probabilities are calculated at the means of the expected value of profit and the variance of profit. In specification (2), the probabilities are calculated at the means of the expected value of profit and set the variance of profit to be zero.

A Restrictions on Parameters between the Structural Equations and Reduced Form Equations

Table A.1: Restrictions on Parameters between the Structural Equations and Reduced Form Equations

$\eta_1 = \tilde{\beta}^F + \lambda_0^F + \lambda_1^F - \lambda_1^N - \lambda_3^N$	$\eta_{16} = -(\lambda_1^N + \lambda_3^N)$
$\eta_2 = -(\lambda_2^N + \lambda_3^N)$	$\eta_{17} = \tilde{\beta}^F + \lambda_0^F + \lambda_2^F - \lambda_2^N - \lambda_3^N$
$\eta_3 = \lambda_2^F + \lambda_3^F + \lambda_3^N$	$\eta_{18} = \lambda_1^F + \lambda_3^F + \lambda_3^N$
$\eta_4 = \tilde{\beta}^I + \lambda_0^I + \lambda_1^I - \lambda_1^N - \lambda_3^N$	$\eta_{19} = -(\lambda_1^N + \lambda_3^N)$
$\eta_5 = -(\lambda_2^N + \lambda_3^N)$	$\eta_{20} = \tilde{\beta}^I + \lambda_0^I + \lambda_2^I - \lambda_2^N - \lambda_3^N$
$\eta_6 = \lambda_2^I + \lambda_3^I + \lambda_3^N$	$\eta_{21} = \lambda_1^I + \lambda_3^I + \lambda_3^N$
$\eta_7 = \tilde{\beta}^I + \lambda_0^B + \lambda_1^B - \lambda_1^N - \lambda_3^N$	$\eta_{22} = -(\lambda_1^N + \lambda_3^N)$
$\eta_8 = -(\lambda_2^N + \lambda_3^N)$	$\eta_{23} = \tilde{\beta}^B + \lambda_0^B + \lambda_2^B - \lambda_2^N - \lambda_3^N$
$\eta_9 = \lambda_2^B + \lambda_3^B + \lambda_3^N$	$\eta_{24} = \lambda_1^B + \lambda_3^B + \lambda_3^N$
$\eta_{10} = \lambda_3^N$	$\eta_{25} = \lambda_3^N$
$\eta_{11} = \lambda_3^N$	$\eta_{26} = \lambda_3^N$
$\eta_{12} = \lambda_3^N$	$\eta_{27} = \lambda_3^N$
$\eta_{13} = \lambda_3^N$	$\eta_{28} = \lambda_3^N$
$\eta_{14} = \lambda_3^N$	$\eta_{29} = \lambda_3^N$
$\eta_{15} = \lambda_3^N$	$\eta_{30} = \lambda_3^N$

Note: There are 15 structural parameters and 30 reduced form coefficients.

B Variability of Farmer's Production

B.1 Variance of Yield

The detailed steps for obtaining the variance of yield are,

$$(56)\quad \begin{aligned} var\{y_{ijt}\} &= var\{\beta_t^N + \boldsymbol{x}_{ijt}\boldsymbol{\gamma} + \tilde{\beta}^F h_{ijt}^F + \tilde{\beta}^I h_{ijt}^I + \tilde{\beta}^B h_{ijt}^B \\ &\quad + \theta_{ij} + \theta_{ij}^F h_{ijt}^F + \theta_{ij}^I h_{ijt}^I + \theta_{ij}^B h_{ijt}^B + e_{ijt}\} \\ &= var\{\beta_t^N\} + var\{\boldsymbol{x}_{ijt}\boldsymbol{\gamma}\} + var\{\tilde{\beta}^F h_{ijt}^F\} + var\{\tilde{\beta}^I h_{ijt}^I\} + var\{\tilde{\beta}^B h_{ijt}^B\} \\ &\quad + var\{\theta_{ij}\} + var\{\theta_{ij}^F h_{ijt}^F\} + var\{\theta_{ij}^I h_{ijt}^I\} + var\{\theta_{ij}^B h_{ijt}^B\} + var\{e_{ijt}\} \\ &= \boldsymbol{\gamma^2} var\{\boldsymbol{x}_{ijt}\} + (\tilde{\beta}^F)^2 var\{h_{ijt}^F\} + (\tilde{\beta}^I)^2 var\{h_{ijt}^I\} + (\tilde{\beta}^B)^2 var\{h_{ijt}^B\} \\ &\quad + var\{\theta_{ij}\} + var\{\theta_{ij}^F h_{ijt}^F\} + var\{\theta_{ij}^I h_{ijt}^I\} + var\{\theta_{ij}^B h_{ijt}^B\} + var\{e_{ijt}\}. \end{aligned}$$

The second equality is based on the independence of each term. The third equality is due to the feature of a structural model - the true values of all βs are constant.

B.2 Conditional Variance of Yield

The detailed steps for obtaining the conditional variance of yields are,

$$(57)\quad \begin{aligned} & Var\{y_{ijt}|\boldsymbol{x}_{ijt}, h_{ijt}^D\} \\ &= \boldsymbol{\gamma^2} Var\{\boldsymbol{x}_{ijt}|\boldsymbol{x}_{ijt}, h_{ijt}^D\} + (\tilde{\beta}^F)^2 Var\{h_{ijt}^F|\boldsymbol{x}_{ijt}, h_{ijt}^D\} + (\tilde{\beta}^I)^2 Var\{h_{ijt}^I|\boldsymbol{x}_{ijt}, h_{ijt}^D\} \\ &\quad + (\tilde{\beta}^B)^2 Var\{h_{ijt}^B|\boldsymbol{x}_{ijt}, h_{ijt}^D\} + Var\{\theta_{ij}|\boldsymbol{x}_{ijt}, h_{ijt}^D\} + Var\{\theta_{ij}^F h_{ijt}^F|\boldsymbol{x}_{ijt}, h_{ijt}^D\} \\ &\quad + Var\{\theta_{ij}^I h_{ijt}^I|\boldsymbol{x}_{ijt}, h_{ijt}^D\} + Var\{\theta_{ij}^B h_{ijt}^B|\boldsymbol{x}_{ijt}, h_{ijt}^D\} + Var\{e_{ijt}|\boldsymbol{x}_{ijt}, h_{ijt}^D\} \\ &= Var\{\theta_{ij}|\boldsymbol{x}_{ijt}, h_{ijt}^D\} + Var\{\theta_{ij}^F h_{ijt}^F|\boldsymbol{x}_{ijt}, h_{ijt}^D\} \\ &\quad + Var\{\theta_{ij}^I h_{ijt}^I|\boldsymbol{x}_{ijt}, h_{ijt}^D\} + Var\{\theta_{ij}^B h_{ijt}^B|\boldsymbol{x}_{ijt}, h_{ijt}^D\} + Var\{e_{ijt}|\boldsymbol{x}_{ijt}, h_{ijt}^D\} \\ &= Var\{e_{ijt}|\boldsymbol{x}_{ijt}, h_{ijt}^D\}. \end{aligned}$$

The third equality is because $Var\{X|X\} = 0$. The fourth equality comes from the the assumption that θ_{ij}, θ_{ij}^F, θ_{ij}^I, and θ_{ij}^B are fixed unobserved farmer-plot characteristics, such as $Var\{\theta_{ij}^D\} = 0$.

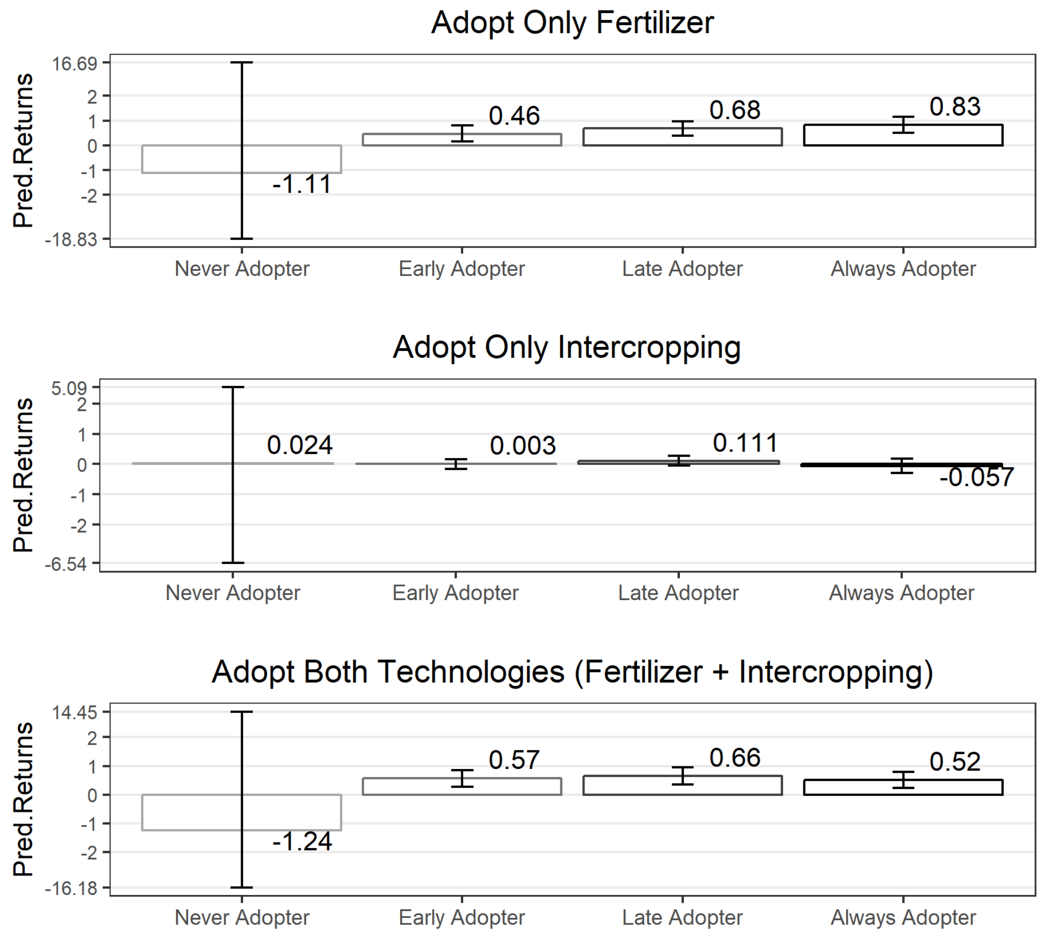
After substituting the definition of error term in to the previous equation, I get the elaborated conditional variance of yields as

$$
\begin{aligned}
(58) \qquad & Var\{y_{ijt}|\boldsymbol{x}_{ijt}, h^D_{ijt}\} = Var\{e_{ijt}|\boldsymbol{x}_{ijt}, h^D_{ijt}\} \\
= \ & Var\{\sum_{d\in D}(\alpha^d)^{\frac{1}{2}} h^d_{ijt}\varepsilon_{ijt}|\boldsymbol{x}_{ijt}, h^D_{ijt}\} \\
= \ & \sum_{d\in D} Var\{(\alpha^d)^{\frac{1}{2}} h^d_{ijt}\varepsilon_{ijt}|\boldsymbol{x}_{ijt}, h^D_{ijt}\} \\
= \ & \sum_{d\in D}\{E[((\alpha^d)^{\frac{1}{2}} h^d_{ijt}\varepsilon_{ijt})^2] - [E((\alpha^d)^{\frac{1}{2}} h^d_{ijt}\varepsilon_{ijt})]^2|\boldsymbol{x}_{ijt}, h^D_{ijt}\} \\
= \ & \sum_{d\in D}\{E[((\alpha^d)^{\frac{1}{2}} h^d_{ijt})^2]E[\varepsilon^2_{ijt}] - [E((\alpha^d)^{\frac{1}{2}} h^d_{ijt})E(\varepsilon_{ijt})]^2|\boldsymbol{x}_{ijt}, h^D_{ijt}\} \\
= \ & \sum_{d\in D}\{E[((\alpha^d)^{\frac{1}{2}} h^d_{ijt})^2]|\boldsymbol{x}_{ijt}, h^D_{ijt}\} \\
= \ & \sum_{d\in D}\{E[\alpha^d(h^d_{ijt})^2]|\boldsymbol{x}_{ijt}, h^D_{ijt}\} \\
= \ & E[\alpha^N(h^N_{ijt})^2|\boldsymbol{x}_{ijt}, h^D_{ijt}] + E[\alpha^F(h^F_{ijt})^2|\boldsymbol{x}_{ijt}, h^D_{ijt}] \\
& +E[\alpha^I(h^I_{ijt})^2|\boldsymbol{x}_{ijt}, h^D_{ijt}] + E[\alpha^B(h^B_{ijt})^2|\boldsymbol{x}_{ijt}, h^D_{ijt}] \\
= \ & E[\alpha^N h^N_{ijt}|\boldsymbol{x}_{ijt}, h^D_{ijt}] + E[\alpha^F h^F_{ijt}|\boldsymbol{x}_{ijt}, h^D_{ijt}] \\
& +E[\alpha^I h^I_{ijt}|\boldsymbol{x}_{ijt}, h^D_{ijt}] + E[\alpha^B h^B_{ijt}|\boldsymbol{x}_{ijt}, h^D_{ijt}],
\end{aligned}
$$

where $E[\varepsilon^2_{ijt}] = 1$ because $Var[\varepsilon_{ijt}] = E[\varepsilon^2_{ijt}] - [E(\varepsilon_{ijt})]^2 = 1$ and $E(\varepsilon_{ijt}) = 0$.

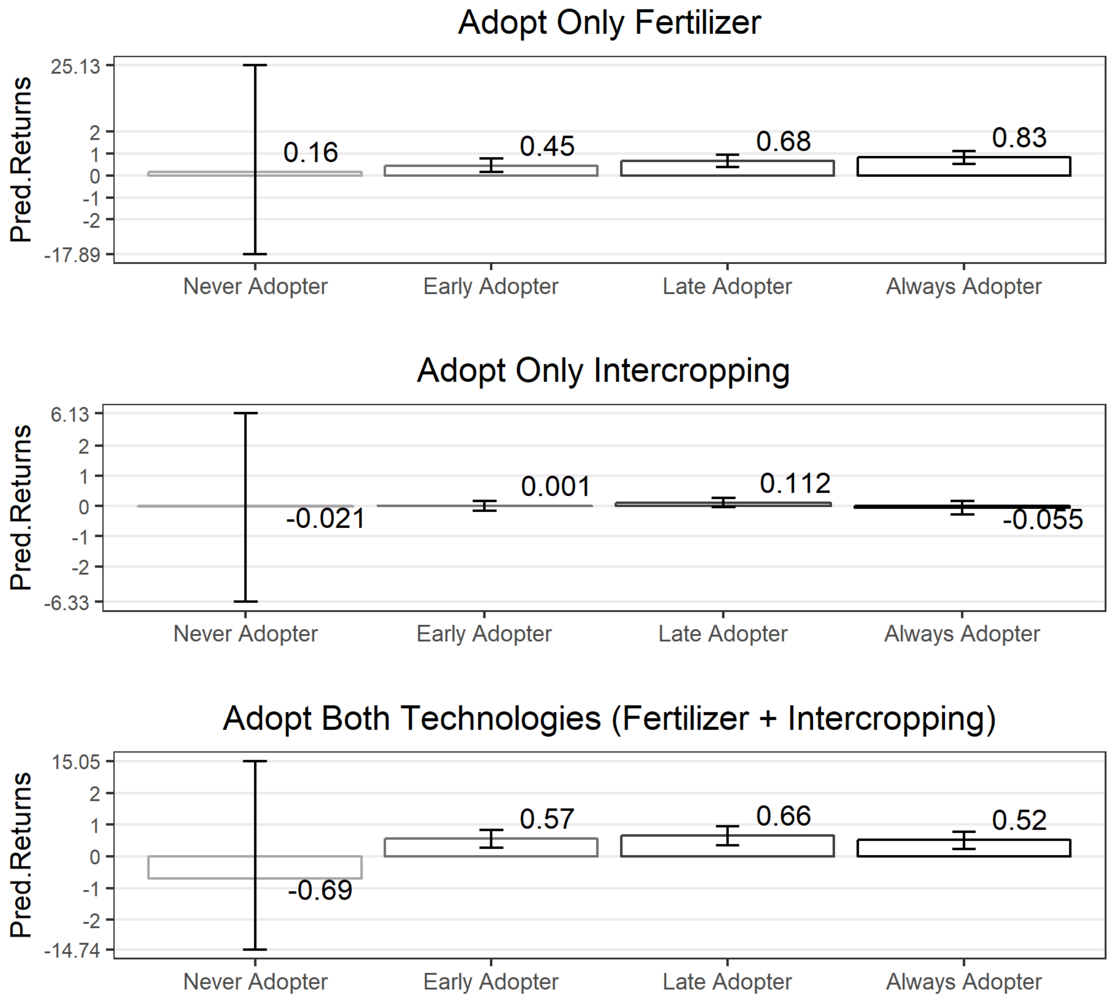
C Figures

Figure C.1: Distribution of Predicted Returns to Adoptions



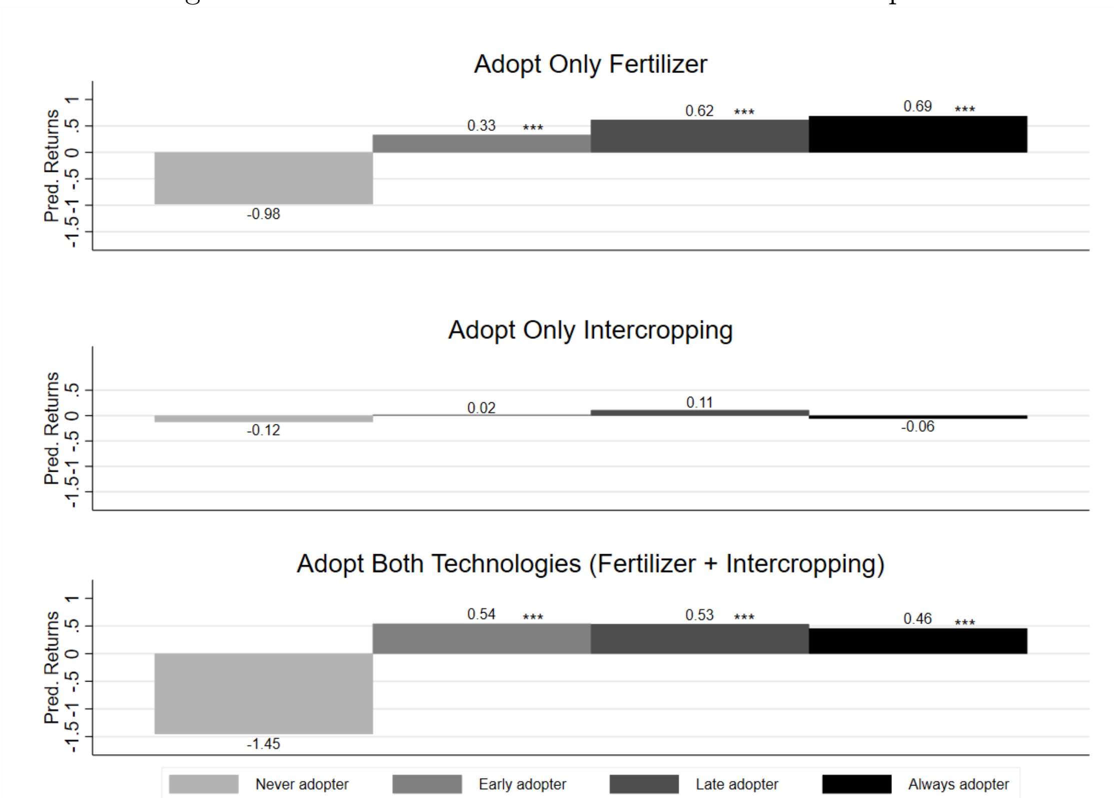
Note: This figure is created using all plots from the analysis sample. Never adopter refers to farmer who adopted the technology in neither farming season; early adopter refers to farmer who adopted the technology in the first farming season but not in the second farming season; late adopter refers to farmer who adopted the technology in the second farming season but not in the first farming season; always adopters refers to farmer who adopted the technology in both farming seasons. The boxes represent predicted returns, which are calculated as $\beta + \theta$. The bars represent the 95% confidence levels, which are calculated through bootstrapping 3075 iterations.

Figure C.2: Distribution of Predicted Weighted Returns to Adoptions



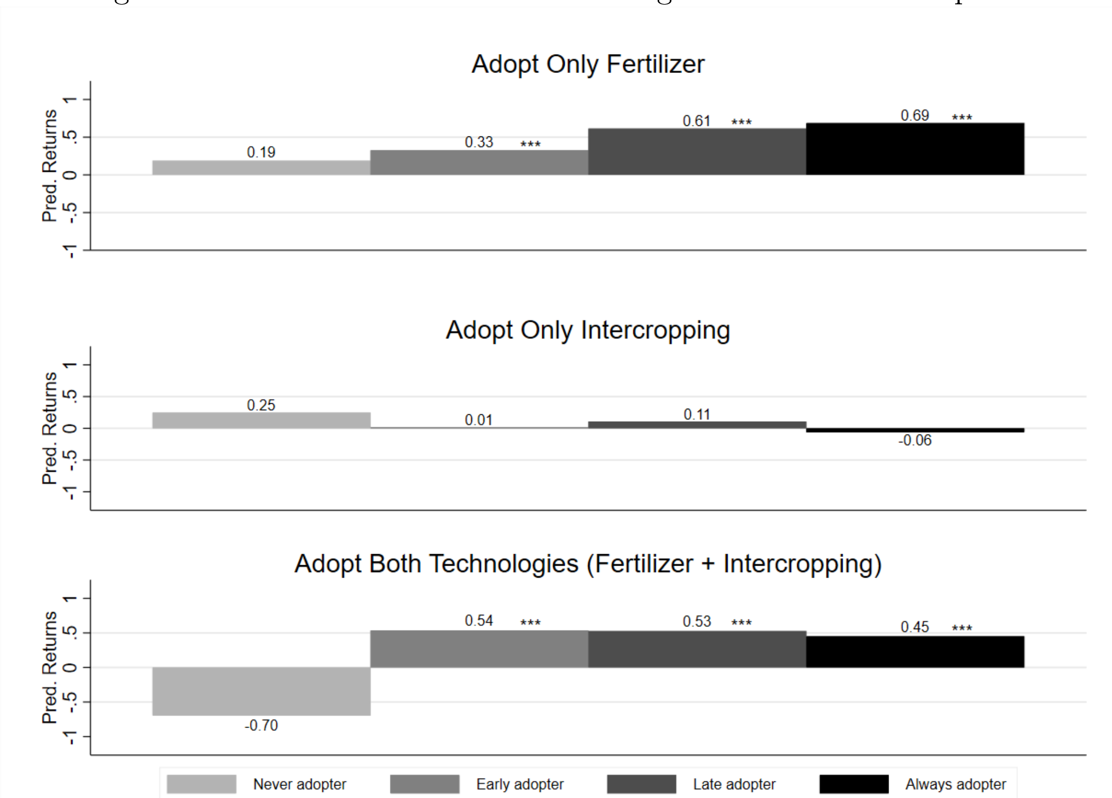
Note: This figure is created using all plots from the analysis sample. Never adopter refers to farmer who adopted the technology in neither farming season; early adopter refers to farmer who adopted the technology in the first farming season but not in the second farming season; late adopter refers to farmer who adopted the technology in the second farming season but not in the first farming season; always adopters refers to farmer who adopted the technology in both farming seasons. The boxes represent predicted returns, which are calculated as $\beta + \theta$. The bars represent the 95% confidence levels, which are calculated through bootstrapping 3050 iterations.

Figure C.3: Distribution of Predicted Returns to Adoptions



Note: This figure is created using plots which have grown at least one of the three most common crops (maize, paddy, beans) in both farming seasons from the analysis sample. Never adopter refers to farmer who adopted the technology in neither farming season; early adopter refers to farmer who adopted the technology in the first farming season but not in the second farming season; late adopter refers to farmer who adopted the technology in the second farming season but not in the first farming season; always adopters refers to farmer who adopted the technology in both farming seasons. The boxes represent predicted returns, which are calculated as $\beta + \theta$.

Figure C.4: Distribution of Predicted Weighted Returns to Adoptions



Note: This figure is created using plots which have grown at least one of the three most common crops (maize, paddy, beans) in both farming seasons from the analysis sample. Never adopter refers to farmer who adopted the technology in neither farming season; early adopter refers to farmer who adopted the technology in the first farming season but not in the second farming season; late adopter refers to farmer who adopted the technology in the second farming season but not in the first farming season; always adopters refers to farmer who adopted the technology in both farming seasons. The boxes represent predicted returns, which are calculated as $\beta + \theta$.

D Tables

Table D.1: Descriptive Statistics - Conditional Expected Value of Yield and Conditional Variance of Yield

Panel A: Expected Value of	N	Mean	S.D.
log of yield			
Adopt neither technology	5046	4.48	0.48
Adopt only fertilizer	5046	4.70	0.50
Adopt only intercropping	5046	4.47	0.47
Adopt both technologies	5046	3.95	0.63
yield			
Adopt neither technology	5046	114.90	54.29
Adopt only fertilizer	5046	148.42	73.68
Adopt only intercropping	5046	111.89	52.36
Adopt both technologies	5046	74.85	61.94

Panel B: Variance of	N	Mean	S.D.
log of yield			
Adopt neither technology	5046	0.32	
Adopt only fertilizer	5046	0.38	
Adopt only intercropping	5046	0.28	
Adopt both technologies	5046	0.29	
yield			
Adopt neither technology	5046	6158.58	9418.00
Adopt only fertilizer	5046	12627.42	18361.06
Adopt only intercropping	5046	5001.87	7493.69
Adopt both technologies	5046	3169.33	7373.44

Note: The descriptive statistics are created using the analysis sample.

Table D.2: Descriptive Statistics - Technology Adoption Rates for Various Crops

Panel A: Farming season 2010-2011						
	Adoption Rate of Technology over All Plots Grown Certain Crop					
Crop	Neither	Fertilizer	Intercropping	Both	# of Plots	% of Plots
Maize	27.53%	7.18%	53.93%	11.36%	2368	39.47%
Rice	74.05%	10.02%	14.72%	1.21%	659	10.98%
Beans	11.62%	2.91%	64.83%	20.64%	654	10.90%
Groundnut	20.38%	2.19%	66.14%	11.29%	319	5.32%
Sorghum	29.94%	0.00%	69.11%	0.96%	314	5.23%
Sweet Potatoes	31.39%	2.24%	61.43%	4.93%	223	3.72%
Cow Pea	6.78%	0.56%	83.05%	9.60%	177	2.95%
Pigeon Pea	5.88%	0.59%	78.82%	14.71%	170	2.83%
Sunflower	14.97%	1.36%	64.63%	19.05%	147	2.45%

Panel B: Farming season 2012-2013						
	Adoption Rate of Technology over All Plots Grown Certain Crop					
Crop	Neither	Fertilizer	Intercropping	Both	# of Plots	% of Plots
Maize	28.03%	6.46%	55.89%	9.61%	3079	38.84%
Beans	13.58%	2.19%	66.97%	17.26%	869	10.96%
Rice	68.57%	10.81%	18.76%	1.86%	805	10.15%
Groundnut	20.55%	0.64%	67.37%	11.44%	472	5.95%
Sweet Potatoes	35.99%	0.82%	57.97%	5.22%	364	4.59%
Sorghum	33.33%	0.31%	63.58%	2.78%	324	4.09%
Pigeon Pea	5.07%	0.36%	88.77%	5.80%	276	3.48%
Sunflower	21.14%	1.22%	57.32%	20.33%	246	3.10%
Cow Pea	6.56%	0.00%	85.66%	7.79%	244	3.08%

Note: The descriptive statistics are created using the analysis sample.