GENDER AND DYNAMICS OF TECHNOLOGY ADOPTION: EVIDENCE FROM UGANDA

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ABSTRACT

Technology adoption is seen as an important tool for increasing agricultural efficiency and combating food insecurity. Despite this theory, Sub-Saharan Africa, which suffers from one of the highest rates of food insecurity, has one of the lowest rates of technology adoption. This is especially prevalent among female headed households. Accordingly, the objective of this paper is to investigate the dynamics of technology adoption at household level and further disaggregate it by gender. Using four waves of Ugandan household level panel data, we find that technology adoption in the first period is the primary determinant of technology adoption in the subsequent periods. Gender level analysis shows that this finding is dominant by male headed households who make the majority of the sample. In contrast, lagged technology adoption is the main driver of adoption for female headed households.

Key Words – technology adoption, food insecurity, panel data, dynamic estimation, Uganda

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1. INTRODUCTION

Hunger kills more people every year than AIDS, malaria and tuberculosis combined (World Food Programme 2015). Among regions most suffering from hunger, Sub-Saharan Africa (SSA) has the highest prevalence of food insecurity, with 25% of the population malnourished (WFP 2015). To add to the issue, agricultural outputs have reduced over the last decade in many economies of this region (Suri 2011). There is evidence that adoption of improved agricultural production technologies can increase yields significantly (Karanja, Jayne, and Strasberg 1998; Minten and Barrett 2008). For example, maize yields in Kenya, India and Mexico were similar in the 1960's, ranging between 10,000 to 12,000 hg/ha. The yields rose by 2.6% and 1.4% in India and Mexico, respectively due to the Green Revolution, it decreased by 1.2% in Kenya in the 2000's (Suri 2011). Despite the apparent advantages of modern technology adoption and its widespread availability in the region, its adoption has been rather slow in SSA.

Among farmers that have low rates of technology adoption, female farmers form the majority of non-adopters. This poses a hindrance to agricultural efficiency in SSA, where females make up 50% of the agricultural labor force, significantly contributing to the production process (Food and Agriculture Organization of the United Nations (FAO) 2011). Despite their high participation, female have lower access to productive resources and opportunities, for example, land, livestock, labor, education, extension and financial services, and technology. This problem not only impacts these agricultural women, but also imposes costs of inefficiency on the agriculture sector, impacting the society and the regional economy, and aggravating the world food insecurity problem. Leveling the field of access to agricultural resources for male and female could increase female farmers' agricultural yields by 20-30%, increasing the total output up to 4%. This would feed an additional 12–17 % of the world's hungry (FAO 2011).

The contrasting low rates of adoption in the SSA region with those of the more developed countries and of female farmers to those of male farmers is puzzling. This puzzle has created a field of its own in development economics. Credit constraints, access to resources, informational barriers, taste preferences, differences in agroecological conditions, lack of effective commitment devices and learning models are among the reasons to low rates of technology adoption (Conley and Udry 2010; Duflo, Kremer, and Robinson 2008; Foster and Rosenzweig 1995). Moreover, reasons of gender gap in technology adoption have been attributed to differences between male and female farmers in farm size, asset ownership, access to inputs such as land, labor and extension services, and distance to the market (Peterman et al. 2011; Doss and Morris 2000; Gilbert, Sakala, and Benson 2002; Thapa 2008; Tiruneh et al. 2001). The dominant approach has been to assume the technology adoption decision as static. However, farmers may base their current decision of adoption on their past experiences (Suri 2011; Ma and Shi 2015; Dercon and Christiaensen 2011; Besley and Case 1993). For example, Ma and Shi (2015) find that the dynamic model fit their farmers technology decision better than the static model. In addition, they also find that self learning effect is stronger than neighborhood effect in a dynamic setting. These findings highlight the importance of estimating a dynamic empirical adoption model. In another study, using a structural dynamic model, Suri (2011) finds that heterogeneous benefits and costs of technologies determine heterogeneity in adoption patterns among farmers. This implies that households with higher expected net benefits are more likely to adopt technology in the first period and in subsequent periods. On the contrary, households with zero net benefit will move in and out of technology adoption and those with below zero expected benefit will never adopt. Since literature has shown that there are significant heterogeneity in male and female headed households including gaps in technology adoption, this poses the questions: if and how dynamics of technology adoption decisions compare over male and female headed households. The answers to these questions could point us to targeted policy approach to encourage technology adoption among the marginalized households. Accordingly, the objectives of our paper are to empirically investigate dynamics of technology adoption and dig deeper into the dynamics of gender gap in technology adoption using four waves of household level panel data from Uganda. To the best our knowledge, we are the first to study the dynamics of technology adoption by incorporating gender.

In order to motivate our empirical analysis, we devise a simple dynamic model of technology adoption. Then, we formulate empirical models, which we estimate in three phases. First, we use lagged dependent variables to account for the dynamic nature of technology adoption and employ Dynamic Probit models. Second, we use CML Probit to account for technology adoption in the first period. Third, we replicate the earlier methods to investigate the dynamics of technology adoption for male and female headed households separately. We find the following: (i) For combined household analysis (i.e. male and female headed households together), technology adoption in the first period is the primary determinant of technology adoption in the following periods. This conclusion is mainly driven by the male headed households who make the majority of the sample and have higher endowments. (ii) For female headed households, they are less likely to adopt technology in the first period as they have lower endowments. In fact, lagged technology is the main driver of adoption for them, indicating that female headed households are more likely to move in and out of adoption status depending on their most recent experience with technology adoption. (iii) The poorest of the households are likely to never adopt.

These results have important policy implications. Because adopting technology in the current period is the key determinant of adopting in the later periods, technology adoption environments (initial conditions) should be made favorable for the marginalized households when introducing modern technology in the market, so that households gain positive experience from adoption through increased agricultural efficiency. This means that policy makers should increase female's access to farming plots, off farm income, literacy, extension services and training programs on modern technology use.

The remainder of this paper is structured as follows. Section 2 discusses relevant empirical literature and Section 3 provides the institutional context and importance of technology adoption in Uganda, and discusses the data. Section 4 discusses a theoretical framework of adoption decision and empirical model. Section 5 provides the results and Section 6 concludes.

2. LITERATURE REVIEW

In the seminal paper of technology adoption, Griliches (1957) studies heterogeneity in the local conditions that determine the adoption speeds of hybrid corn in the Midwestern US. He finds that in addition to expected profits and scale, the adoption rates are determined by the presence of the technology suppliers and the seed's adaptability to local conditions. In addition, studies have found that heterogeneity in education of the farmers, soil quality, agroclimatic conditions, manure use, hiring of labor and extension services, cost and availability of seeds, credit constrains are the determinants of use of technology such as fertilizer and improved seed (Ouma et al. 2002; Schultz 1963; Knight, Weir, and Woldehanna 2003; Makokha et al. 2001). Credit constraint has also been cited as the main hindrance of technology adoption in Croppenstedt, Demeke, and Meschi (2003)'s fertilizer adoption model of Ethiopia, and Salasya et al. (1998)'s fertilizer adoption in Western Kenya.

Recent literature has also focused on technology adoption decisions due to social interaction such as learning externalities. Besley and Case (1993) describe the empirical approaches to analyze technology adoption in this regard. Using a household level panel data from a nationally representative sample of rural India, Foster and Rosenzweig (1995) find that imperfect knowledge about the management of new high-yielding variety (HYV) seeds act as barriers to its adoption. However, these barriers diminish as farmers' experience increase due to their own experiences as well as their neighbors' experiences. Using data on farmers' communication pattern in Ghana, Conley and Udry (2010) find that farmers follow the input patterns of their informational neighbors who were successful in previous periods. Munshi (2004) further finds that the impact of learning from self versus others depends on the kinds of seeds that farmers use. For example, wheat growers respond strongly to their neighbor's experience but rice farmers experiment themselves. This is because rice HYVs are sensitive to soil characteristics and managerial inputs, creating heterogeneity in production across farmers. Similarly, using data on a high-yielding, low external input rice production method in Madagascar, Moser and Barrett (2006) find that while seasonal liquidity constraints discourage adoption by poorer farmers, learning effects, both from other farmers and extension agents, significantly influence farmers' technology adoption decisions.

Apart from the factors mentioned earlier, studies have also found differences in technology adoption by gender. For example, using data from Ghana, Doss and Morris (2000) found that female farmers in female headed households were less likely to adopt modern maize seed varieties and fertilizer. This difference was attributed to gender differences in access to complementary inputs, especially land, labor, and extension services. Kilic, Palacios-López, and Goldstein (2015) find a 25% higher productivity in male managed farms in case of Malawi. These gaps existed due to lower inorganic fertilizer use by female plot managers who mainly farmed food crops as opposed to export crops by male farm managers. Gilbert, Sakala, and Benson (2002) conducted a gender analysis of cropping system in Malawi. They found that males had greater experience as heads of the households, used higher amounts of fertilizer and primarily grew cash crops. Likewise, another study by Due and Gladwin (1991) found that male headed households used significantly higher amounts of fertilizer with higher intensity and had larger average landholding size than female headed households. They concluded that social constrains coupled with institutional barriers limited the participation of female farmers in farmers' clubs, reducing their access to credit and hindering the adoption levels of fertilizer. Furthermore, Smale and Mason (2012) find that quality and quantity (i.e. education and supply) of labor, number of dependents in the household, temperature, information source, and length of residence in the community are associated with significant differences in maize hybrids adoption between male and female headed households. Similarly, using separate models for male and female headed households, Diiro, Ker, and Sam (2015) find that education and distance to the market were primary determinants of inorganic fertilizer adoption in Uganda. Separating the farmers by the gender of their household heads and the gender of farmers, Fisher and Kandiwa (2014) find that female household heads had an 11% lower probability, and wives of male headed households had a 12% lower probability of adopting modern maize than male household heads. On the contrary, Tanellari et al. (2014) find that differences in rates of improved variety of peanut is insignificant between male and female farmers of the same households, however, it differs for female farmers in the female headed households. In a review of literature on female farmers, Quisumbing and Pandolfelli (2010) report a study on Tanzania, where female farmers are less likely to have access to new markets because agricultural companies approach males, assuming that males are the primary producers in the household.

Although the existing literature extensively covers the determinants of technology adoption and gender gaps, there is limited literature in the field of dynamics of technology adoption and none that incorporate gender. For the former, Dercon and Christiaensen (2011) present a theoretical dynamic model of how a household's capacity of protecting itself ex post (from falling consumption) affects its ex ante risk taking in agriculture i.e. technology adoption decisions. Using panel data, the authors control for household heterogeneity, however, the empirical estimation does not account for decision making as a dynamic process. In another study, Suri (2011) uses a structural dynamic model and finds that heterogeneous benefits and costs of technologies determine the adoption patterns among farmers. For example, although farmers may have highest estimated gross returns, they are correlated with high costs of acquiring technology, which causes them not to use hybrid seeds. In contrast, farmers with high net returns adopt and those with zero marginal returns move in and out of technology adoption. Finally, Ma and Shi (2015) construct a continuous choice dynamic model, where forward looking farmers experiment with a new technology on part of their land to learn about its profitability. Using data on the US soybean farmers, they find that the dynamic model fits the data better, highlighting the importance of estimating a dynamic empirical adoption model that is consistent with farmers' underlying decision process. Moreover, they also find that self learning effect is stronger than neighborhood effect in a dynamic setting. The findings in our study parallel the latter two studies. In addition to these findings, we also find that technology adoption is highly determined by adoption in the first period (more details later in Section 5).

3. INSTITUTIONAL CONTEXT AND DATA

The Ugandan agricultural sector employs over 66% of the working population, of which over 55% consists of female labor, making an overall contribution of 22.5% to the national GDP (Uganda Ministry of Agriculture, Animal Industry and Fisheries 2011). As per the Ministry (2011), Ugandan economic growth is hampered by low productivity of the agriculture sector; estimated at only 0.9% in 2010/11 compared to a growth of 2.4% in 2009/10 well below the government-set growth target of 6%. Uganda's poor soil quality combined with infrequent use of modern technologies are some of the major causes of low yields (Shively and Hao 2012). Ugandan farmers rank low in technology adoption in both fraction and intensity. For example, only 7 to 8% of Ugandan farmers used fertilizers in 2009 (Yamano and Arai 2011), compared to about 17 to 31% in neighboring Kenya (Suri 2011). Moreover, an average Ugandan farmer applies about 2.1 kg of fertilizer per hectare in contrast to 32.4 kg per hectare by a Kenyan farmer (Greensand 2011).

Uganda was engaged in civil conflicts and incapable of instrumenting effective agricultural policies while its neighbor Kenya was heavily distributing fertilizers in 1970-1980, (Yamano and Arai 2011). When the Museveni government took over in 1986, it quickly adopted policies of other African countries that were focused on structural adjustment programs. Despite its market reform policies, lack of basic market structure hindered the inception of a large scale fertilizer market and thus, benefits from scale economies. The fertilizer market was dominated by small-scale trade, suffered from high prices and low net margins in the early 2000s due to the poor transportation infrastructure and Uganda's inaccessibility from the major ports (Omamo 2003). Recognizing the need for modernizing the agricultural sector, the Government of Uganda together with its development partners is implementing the Development Strategy and Investment Plan (DSIP) with an objective to develop agricultural technologies through research and strengthen agricultural research institutions (Uganda Bureau of Statistics 2013). The hope is to modernize the agricultural sector and encourage the use of modern technology and hence implement large scale commercial farming.

3.1 Data and Descriptive Analysis

The data for this study comes from one wave of Uganda National Household Survey (UNHS) 2005/06 and three waves of Uganda National Panel Survey (UNPS) from 2009/10 to 2011/12, conducted by the Uganda Bureau of Statistics (UBOS). The objective of the UNHS was to collect high quality data on demographic, social and economic characteristics of the household. Altogether 7,417 households were surveyed nationally, among which 5,877 were agricultural households. In particular, the UNHS 2005/06 had an agricultural module, which aimed to provide a deeper insight into factors affecting farm incomes and understand the breadth of farmers' resources and marketing opportunities. This would inform decision-makers in areas of the Plan for Modernization of Agriculture (PMA), Poverty Eradication Action Programme (PEAP) and other agencies for targeted solutions to low farm incomes. The Module collected data on land, crop area, inputs, outputs, livestock, poultry, and agricultural extension services and technologies.

The UBOS started the UNPS to effectively monitor outcomes of the National Development Strategy (NDS), with financial and technical support from the Government of Netherlands, and the World Bank Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA) project (UGANDA BUREAU OF STATISTICS 2013). The UNPS is done annually, over a twelve-month period on a nationally representative sample of households. The UNPS 2009/2010 surveyed 3,123 households out of the 7,400 households surveyed in the UNHS 2005/06. Out of which, 2,607 were successfully interviewed. Following attrition and new split-off households, the UNPS 2010/11 and UNPS 2011/12 surveyed 2,564 and 2,356 households, respectively. The UNPS provides information for monitoring the National Development Strategy, of major programs such as National Agricultural Advisory Services (NAADS) and General Budget Support by collecting high quality data on income dynamics at the household level to monitor poverty, health outcomes, agricultural inputs, and intervention impact evaluations that are not present in the existing national household surveys.

Our study utilizes the above mentioned four waves of the Uganda data. In particular, we use sections of data from household identification, agricultural inputs, outputs, household assets, income, demographics, systematic and idiosyncratic shocks and extension services. After performing data cleaning and appending for all four waves of data collection, we are left with 9,360 observations from Season 1 and 8,422 from Season 2. Because the nature of crops and their respective agroclimatic conditions differ by season, we further separate the dataset by seasons. The number of observations for Season 1 is greater than that of Season 2 and hence, we choose the former as our primary means for analysis. Further dropping missing variables and households that are not common across the four waves, we end up with a total of 6,688 observation points, with 1,672 observations per year.

In principle, technology use could be a continuous variable in terms of quantities of inputs used but due to challenges of data quality on their quantities, we take technology adoption to be binary throughout the paper. The UNPS collected data on three kinds of technology adoption: hybrid seed, inorganic fertilizer and pesticides. Due to incredibly low rates of adoption when separating by kinds of technology and gender, we define technology adoption to be one if the farmer used any of the three sources of technology, and zero otherwise.[2]

[Table 1 about here]

Table 1 presents the dynamics of technology adoption over time. Overall, a total of 26% of the Ugandan households use technology over the four waves of data collection. Looking at the adoption patterns over the waves, we note that households that adopted technology in any particular period are more likely to adopt technology the following period (with an exception of 2009/10). Likewise households that do not adopt technology in any particular period are more likely to not adopt technology in the following period. This indicates that the nature of technology adoption is dynamic and should be modeled accordingly.

[Table 2 about here]

Table 2 presents summary statistics of variables used in the empirical analysis by wave and technology adoption status. Based on the literature review in Section 2, we select farm income, off-farm income, risk preferences represented by age of the household head, education, represented by aggregate literacy of the household members, farm size, represented by number of plots, wealth, represented by livestock value, household labor, represented by household size, extension services, represented by total number of extension visits, household's participation in NAADS training program, weather shocks (i.e. drought, flood and landslides), health shocks (i.e. death and illness), other shocks (i.e. job loss, theft, fire, violence, crop pests, livestock pests, etc.),

[2] As per author's calculations, where technology adoption is defined as adoption of either one of: inorganic fertilizer, hybrid seed and pesticides.

geographical location (region) and wave of survey. The differences between the households that adopt and do not adopt technology generally follow the economic intuition for all the waves. For example, the means of number of plots farmed by technology adopters are significantly higher than non-adopters for all four waves. Figure 1 depicts this relationship graphically, where the fraction of households adopting technology increase with increasing number of plots.

[Insert Figure 1 here]

Although the nonagricultural income (defined by remittances, wage income and transfers) and livestock value are higher for adopters than non-adopters, the differences are barely significant over the waves. In contrast, farm income is significantly higher for adopters than non-adopters. Furthermore, technology adopters tend to have bigger household size and younger household heads (with an exception of 2010/11 for the latter). Similarly, adopters have higher number of literate household members, higher frequency of extension visits and higher participation in the NAADS training program than non-adopters. When it comes to experiencing systematic (i.e. weather related) or idiosyncratic shocks (i.e. health shocks), we do not find any significant differences between the adopter and non-adopter households at average. The differences in proportion of male household heads across the adopter and non-adopter households are significant across all the years with higher proportion of male heads in the former category. This difference merits further discussion of its own.

[Table 3 about here]

[Figure 2 about here]

Table 3 and Figure 2 present the heterogeneity in technology use across households by gender of the household head. They show that gaps in technology adoption between male and female headed households are persistent across the years. In particular, the fraction of male headed households have 29% adoption and female headed households have 19% adoption at average. In order to delve further into the heterogeneity between the male and female headed households that may have caused the differences in adoption, Table 4 presents summary statistics of the variables in Table 3 by gender of the household head separated by waves.

[Insert Table 4 about here]

As seen earlier, prevalence of technology adoption tends to be significantly different across gender with a positive association with male headed households. As expected, number of plots, income from farm, and livestock value tend to be higher among the male headed households. Similarly, household size and literacy are significantly higher in male headed households (with an exception of 2010/11 for the former). Female household heads tend to be older and receive lower amount of extension visits. Although there are no statistical differences across the waves for weather shocks and other shocks, female headed households tend to experience higher health shocks.

4. THEORETICAL AND EMPIRICAL FRAMEWORK

The aim of this section is to devise a simple dynamic theoretical model and incorporate the gender differences whenever possible in order to motivate our empirical work. Then, devise a model for our empirical estimation based on the dynamic theoretical model. Since household heads are the primary decision makers, let us take a forward looking household head who may be female ($k = 0$) or male ($k = 1$). The household begins each period with a pre-determined liquid wealth, ω, and must decide whether to adopt a modern farm technology, how much to borrow, and how much to consume. Denote $j = 1$ as the decision to adopt and $j = 0$, as the decision to not adopt the modern technology, and let x denote the amount borrowed by the household. The maximum amount b_k that the household may borrow depends on the gender of the household head, with($b_0 < b_1$); that is, a male household may borrow more than a female household. The interest rate on borrowed funds is $r > 0$. We assume that farmers have access to both low-risk low-return and high-risk high-return technology but no access to formal financial markets (i.e. no mechanism to cope with income shortfalls) post production.

Each period, the household receives income from two sources. Farm income, y_j, depends on the farming technology adopted j, where $Ey_1 > Ey_0$ and $Vy_1 > Vy_0$; that is, the modern farming technology promises a higher, but riskier farm income. Off-farm income, z_k, depends on the gender of the household, k, where $Ez_1 > Ez_0$; that is, a male household on average receives a higher off-farm income than a female household. We assume a lower bound for ω, such that: $\varpi \equiv \min\{z_k + y_j\} - (1 + r)b_k > 0$; that is a household's income always exceeds its debt obligation.

The household maximizes the present value of current and expected future utility of consumption over an infinite horizon. The household's dynamic decision problem is thus characterized by a Bellman equation whose value function $V(\omega)$ specifies the maximum expected present value of lifetime utility attainable by the household, given current liquid wealth:

$$V(\omega) = Max_{\{j=0,1;\ 0\leq x\leq b_k\}}\left\{u\left(\omega + x - K_j\right) + \ \delta EV\left(z_k - (1+r)x_1 + y_j\right)\right\} \tag{1}$$

for $\omega \geq \varpi$. Here, $\delta \in (0,1)$ denotes the household's per-period discount factor, K_j is the cost of adopting farming technology j, and u denotes the household's utility, a twice continuously differentiable function of current consumption, with $u' > 0, u'' < 0$, and $u'(0) = -\infty$. Consumption equals the sum of wealth ω and amount borrowed x, less production costs K_j.

Besides the factors considered above, we incorporate other determinants of technology adoption mentioned earlier in Section 3: age of the household head, total household literacy, number of plots, livestock value, household size, total number of extension visits, household participation in NAADS training program, weather shocks, health shocks, other shocks, regional location and time dummy. Let Z_h represent these variables, some of which are assumed to be heterogeneous across the male and female headed households. Following Guizar-Mateos (2013), the intertemporal utility maximization in Equation (1) can be written as follows:

$$V(w) = Max_{\{j=0,1;\ 0\leq x\leq b_k\}}\left\{u\left(\omega + x - K_j;\ Z_h\right) + \ \delta EV\left(z_k - (1+r)x_1 + y_j; Z_h\right)\right\} \tag{2}$$

such that $y_j = f_j(j|Z_h)$ i.e. farm income depends on technology adopted conditional on determinants represented by Z_h.

We use Equation (2) to motivate our empirical analysis. The empirical estimation process follows three phases. First, we use lagged dependent variables to represent the dynamic nature of technology adoption and then employ Dynamic Probit models. However, using a lagged dependent variable violates the strict exogeneity assumption of panel data (Wooldridge 2010). Arellano and Bond (1991) proposed a methodology that eliminates the unobserved effects by taking first differences and then using further lags as instruments for these first difference lagged dependent variables. For non-linear Probit models, obtaining consistent estimators faces the initial conditions problem. This issue arises because of a particular assumption on the relationship between the initial observations (i.e. the baseline survey Y_{i0}) and the unobserved effects, c_i, where i represents a household. Assuming Y_{i0} to be a non-stochastic starting position and the individual time-invariant effects c_i to be independent of the time varying explanatory variables, one could employ a standard probit random effects model to make estimations. This is a rather strong assumption such that the initial state of technology, Y_{i0}, and the unobserved individual heterogeneity c_i are independent. Wooldridge (2010) relaxes this assumption in an alternative approach called the conditional maximum likelihood (CML) estimator, where he allows for correlation between the initial condition and the unobserved individual heterogeneity. A conditional normal distribution is assumed with linear expectation and constant variance. More explicitly, the relationship is modeled as the following:

$$P(Y_{it} = 1|z_{it}, Y_{it-1}, c_i) = \Phi(z_{it}'\theta + \lambda Y_{it-1} + c_i) \tag{3}$$

where z_{it} is set of exogenous explanatory variables, $Y_{it} = 1$ is means that in period *t* the household *i* has adopted the modern technology and Φ is the cumulative standard normal distribution. By the assumption of the distribution of c_i, the latent version of the model can be written as:

$$Y_{it}^* = \psi + \rho Y_{i0} + z_{it}'\theta + \lambda Y_{it-1} + z_i'\delta + \eta_i + \varepsilon_{it} \tag{4}$$

where η_i given (Y_{i0}, z_i) ~ Normal(0,1). This allows us to estimate the parameters using standard RE Probit.

Drawing from Wooldridge (2010), our second method of estimation follows Equation (4), where Y_{i0} is technology adoption in the baseline (i.e. 2005/06), Y_{it-1} is the lagged technology adoption, and *z* comprises of variables from the dynamic model and the literature discussed in Section 3: number of plots planted, farm income, off farm income, value of livestock, gender of the household head, age of the household head, household members' aggregate literary, household size, extension visits, NAADS training program, weather shocks, health shocks, other shocks, regional dummy and time dummy. We note that income and wealth variables, number of plots planted, farm income, off farm income, value of livestock, may violate the assumption of strict exogeneity in Equation (4). Therefore, following common practice in the literature, we use lags of these variables instead of the income variables themselves. Finally, we repeat phases one and two to explore the dynamics of technology adoption for male and female headed households separately.

5. RESULTS AND DISCUSSIONS

To investigate the dynamics of technology adoption, we estimate several variants of our empirical model, which we group in three phases. Phase one employs the Dynamic Probit model as discussed earlier. Phase two employs the CML Probit model in order to account for initial conditions problem and Phase three investigates the dynamics of technology adoption across male and female headed households. In order to progressively build robust results, the estimations within each phase control for regional and wave effects, and account for endogeneity. Subsection 5.1 presents analysis based on Dynamic Probit, 5.2 on CML Probit, followed by a short discussion comparing results from these methods. Finally, Section 5.3 presents gender dynamics estimations. Based on these subsections, we consolidate our key findings in Subsection 5.4 and calculate cumulative marginal effects of technology adoption, followed by discussion and comparison of results across combined and gender disaggregated households.

5.1 Dynamic of technology adoption for combined households using Dynamic Probit

The Dynamic Probit estimates of the technology adoption are presented in Table 5. The first column presents estimates, controlling for various income and household characteristics as well as shocks. This model assumes strict exogeneity of independent variables and does not control for region or wave. The model shows that households that adopt technology in the previous period are 9% more likely to adopt in the following period. As expected, the impacts of income and wealth variables, number of farm plots, off farm income, farm income and livestock value, are significantly positive for technology adoption. Male headed households are more likely to adopt technology and are bigger in household size. This may confirm the labor intensity that is required often when farming with modern technology. Age of the household head is negatively associated with technology adoption, which confirms the risk aversion theory i.e. households that are more risk averse are less likely to experiment with new technology. Similarly, households that have more literate members and members that participate in NAADS training are more likely to adopt technology.

[Insert Table 5 about here]

In the second column, we add region and time dummies and note that the coefficient of lagged technology adoption has gone down from 0.09 to 0.07. This model behaves very similar to the first one such that all the wealth and income variables are still statistically significant and positive. However, the size of the household becomes insignificant and number of extension visits and other shocks become positively and negatively significant, respectively. We will not discuss the magnitudes of these effects as this model still assumes strict exogeneity of the income variables, which is a strong assumption. The last two columns of Table 5 report the results by relaxing the strict exogeneity of the wealth and income variables. Instead of using the income variables, we use their lagged values directly in the model. Model 3 excludes the region and time dummies. We note that the coefficient of lagged technology adoption is in between the ranges of those predicted by Models 1 and 2. The significance of wealth and income variables disappear except for farm income. Male household head, bigger household size, literacy and participation in NAADS training are still significant and positive. Parallel to Models 1 and 2, age of the household head is statistically significant and negative.

The final column adds the region and wave dummies and maintains the endogeneity assumption of wealth and income variables such that we continue using lagged variables in Model 4. Since this is the most conservative model, we propose that the marginal effects of this model are more reliable than those discussed above. The coefficient estimate of lagged technology adoption decreases to 0.065. Parallel to Model 3, farm income is still statistically significant and positive. Among the household characteristics, gender, age, literacy, extension visits and participation in NAADS training are all significant and have expected signs.

Using several variants of the Dynamic Probit model, we find that households' decision to adopt technology in the latter periods is highly determined by their decisions in the previous period. This analysis confirms the descriptive analysis in Section 4, shown by Table 1. As discussed in Section 4, our model may suffer from the endogeneity problem because we are using the lagged technology variable as one of the regressors, so in the second phase of estimation, we use CML Probit.

5.2 Dynamic of technology adoption for combined households using CML Probit

As discussed in Section 4, using the lagged dependent variable violates the strict exogeneity assumption of panel data. Therefore, as discussed in Section 4, we employ CML Probit for estimations in this phase. The empirical estimation is based on Equation (4) and we conduct four sets of estimations following the same procedure as in Subsection 5.1. The results are presented in Table 6.

[Insert Table 6 about here]

Model 1 controls for wealth, income, household characteristics and shocks, and assumes strict exogeneity. The coefficient of lagged technology adoption states that controlling for all the variables mentioned above and for technology adoption in the first period, households that adopt technology in the previous period are 3.9% more likely to adopt in the subsequent period. Likewise, the coefficient on the baseline technology (i.e. technology adoption in round one) indicates that households that adopt technology in the first period are 9% more likely to adopt technology in the latter periods ceteris paribus. The wealth and income variables are positive and statistically significant for technology adoption. Similarly, household size, literacy and participation in NAADS training program are all significant and have expected signs. Although gender of the household head, age and shocks have expected signs (with an exception of health shocks), they are statistically insignificant.

Model 2 is presented in the second column; we add region and time dummies to this model. The coefficient of lagged technology adoption is very similar to the previous model, indicating an impact of 3.8% as opposed to 3.9% earlier. The signs and coefficients of almost all the variables are similar to that of Model 1. However, the coefficient on baseline technology adoption has halved to 4.2%. The region and year dummies have "soaked up" the impacts of technology adoption in the first round. Moreover, we find variations in three variables such that gender of the household head is statistically significant and literacy and participation in training programs are not. Moving away from the assumption of strict exogeneity of the income variables, we present Model 3 in the third column, where we use their lagged values. Excluding the region and time dummies, we find that the significance of lagged technology adoption disappears and the coefficient of baseline technology adoption becomes higher and more significant. The significance of wealth and income variables disappear except for farm income. Among the other covariates, household size and participation in NAADS training remain positive and significant.

In the final column, we add the region and time dummies maintaining the endogeneity assumption of wealth and income variables. Since this is the most conservative model, we propose that the marginal effects of this model are more reliable than the models discussed above. The coefficient estimate of lagged technology adoption remains insignificant but that of baseline technology adoption remains significant and positive. It indicates that households that adopt technology in the first round are 5% more likely to adopt technology in the following years. Parallel to Model 3, farm income is statistically significant and positive. All other covariates become insignificant except for the gender of the household head, indicating that male headed households are 8.4% more likely to adopt technology than female headed households.

Using several variants of the CML Probit, we find that a households' decision to adopt technology in the latter periods is primarily determined by their decisions to adopt in the first period. Comparing the CML Probit estimates to the Dynamic Probit, we find that controlling for technology adoption in the first period "soaks up" the impact due to lagged technology adoption. Assuming that CML Probit is a better estimation procedure, based on our observations so far, we conclude that technology adoption is primarily determined by adoption in the first period, farm income and gender of the household head.

5.3 Dynamics of technology adoption by gender

Since gender of a household is statistically significant in its decision to adopt technology across the board, our third phase of estimation digs deeper into the dynamics of technology adoption by gender. The objective of this estimation phase is to explore if there are any differences in the adoption dynamics between male and female headed households. We follow Subsections 5.1 and 5.2 and separately investigate households' technology adoption choices by gender. We present the analysis of results from the male and female headed households in Subsection 5.3.1 and 5.3.2, respectively.

5.3.1 Dynamic of technology adoption for male headed households

The Dynamic Probit estimates of technology adoption for male headed households are presented in Table 7. Parallel to Subsection 5.1, Models 1 and 2 assume strict exogeneity of independent variables, with added region and wave controls in Model 2. Models 3 and 4 relax this assumption and account for the endogenous income and wealth variables by using lagged variables. In Model 1, all the variables except off-farm income, extension visits and shocks are significant with expected signs. The coefficient on lagged technology states that households that adopt technology in the previous period are 8.5% more likely to adopt in the following period than households that do not adopt technology in the previous period. Model 2 follows the same pattern of significance of variables with an exception of household size, which becomes insignificant after controlling for region and wave. This might be caused by the fact that average household size does not change much over the four waves. The coefficient on our primary variable of interest, lagged technology, decreases to 0.062 compared to 0.085 earlier.

[Insert Table 7 about here]

Accounting for endogeneity and excluding the region and year dummy in Model 3, we find that number of plots and off-farm income are insignificant, however, household size becomes significant. Parallel to Subsection 5.1, the coefficient of lagged technology adoption is in between the ranges of those predicted by Models 1 and 2. All other variables behave as in Model 2. Adding region and wave dummies, the coefficient estimate of lagged technology adoption decreases to 0.05 from 0.06 in Model 2. Farm income, age of the household head, literacy, extension visits and training program remain significant with expected signs. Comparing these estimates with the analysis for combined households in Table 5, we find similar patterns for variables across the four models. Overall, the predictions of Dynamic Probit model suggest that for male headed households, if they adopted technology in the previous (current) period then they are more likely to adopt in the current (next) period compared to the households that did not adopt technology in the previous (current) period. However, we note that this dynamic impact for the male headed households is lower than those in the combined households (Table 5), and for Model 4 lagged technology is only significant at the 10% level. This finding is rather puzzling since we know that male headed households are higher technology adopters than female headed households on average.

We move onto using CML Probit to dig deeper into the above mentioned issue. Table 8 presents marginal effects of technology adoption for male headed households using CML Probit. The four models presented follow the same estimation strategy as in 5.2. Interestingly, we find that lagged technology adoption is insignificant in all these models for male headed households. However, the coefficient on baseline technology adoption indicates that depending on the model specification, male headed households that adopt technology in the first period are 5-10% more likely to adopt technology in the latter periods. As expected, Model 4, which accounts for endogeneity and region and time dummies, gives the most conservative estimate indicating that households that adopt technology in the first period are 4.6% more likely to adopt technology in the latter periods than those that do not adopt technology in the first period. Looking across the models, we find that income variables become insignificant except for farm income.

[Insert Table 8 about here]

Using several variants of the CML Probit, we find that male headed households' decision to adopt technology in the latter periods is determined by their decisions to adopt in the first period. Comparing these estimates with combined household estimates (Table 6), we find that the coefficient on baseline technology adoption for male headed households are very similar to those with combined household estimates. We speculate at this point that male headed households may have dominated the coefficients of the baseline technology adoption and female headed households may have dominated the coefficients of lagged technology adoption. In the next section, we present estimation results from dynamic models of female headed households, which will help us solve the puzzle.

5.3.2 Dynamics of technology adoption for female headed households

The Dynamic Probit estimates of the technology adoption for female headed household are presented in Table 9. The estimation procedures for all four models presented in the table follow those of 5.3.1. In Model 1, we find that off-farm income, farm income, household size, literacy and participation in training program are significant and have expected signs for determining technology adoption. The estimations differ from Model 1 in combined and male headed households (Tables 5, 7), as number of plots, livestock value and age of the household head are insignificant here. This may be a byproduct of the fact that sample size for female headed households is rather small with less than a third of the combined households and less than half of the male headed households. Nevertheless, the coefficient of the lagged technology for female headed households is 0.15 and significant, which is higher than those of combined and male headed households (Tables 5, 7). Parallel to subsection 5.3.1, controlling for region and time in Model 2 makes the household size insignificant, however, other variables follow the same pattern of significance as in Model 1. The coefficient of lagged technology decreases to 0.13 compared to 0.15 earlier.

[Insert Table 9 about here]

Accounting for endogeneity and excluding the region and year dummies in Model 3, we find that off-farm income becomes insignificant, however, household size becomes significant. All other variables behave like those in Model 2, including the coefficient on lagged technology adoption, which remains at 0.13. Adding region and wave dummies in Model 4, the coefficient of lagged technology adoption decreases to 0.12. Farm income, literacy and participation in the NAADS training program remain significant with expected signs. Overall, the predictions of Dynamic Probit suggest that when female headed households adopt technology in the previous (current) period, they are more likely to adopt technology in the current (next) period, as opposed to those households that do not adopt in the previous (current) period.

Comparing these estimates with the combined and male headed households (Tables 5, 7), we find that the coefficients of lagged technology are significantly higher than those in Tables 5 and 7. Although this seems puzzling given higher average technology adoption rates in male headed households, we found in Subsection 5.3.1, technology adoption in the baseline period is the main determinant for male headed households. Therefore, we can speculate that lagged technology adoption may be the primary factor for female headed households, while baseline adoption remains the primary factor for male headed households.

To solve this puzzle, we use CML Probit in the final stage of our estimation procedure. The marginal effects of technology adoption for female headed households are presented in Table 10. The four models in the table follow the same estimation strategy as in Subsection 5.2. Looking across the models, we find that the coefficients on lagged technology adoption range from 0.07 to 0.10, depending on the model specification. As expected, Model 4, which accounts for endogeneity and region and time dummies, gives the most conservative estimate, indicating that female headed households that adopt technology in the previous (current) period are 7.1% more likely to adopt technology in current (next) period than those that do not adopt technology in the previous (current) period. The significance of household size disappears with the addition of time and region dummies and those of the income variables disappear when accounted for their endogeneity. Farm income and literacy remain significant and positive.

[Insert Table 10 about here]

Using several variants of the CML Probit, we find that female headed households' decision to adopt technology in the next period is determined by their decisions to adopt in the current period, which in turn is dependent on their adoption decision in the previous period. Comparing these estimations with the male headed and combined households CML Probit estimates, we find that the coefficient on lagged technology for female headed households are both higher and significant. These results confirm our earlier speculation (end of Subsection 5.3.1) that lagged technology adoption determine technology adoption of female headed households and baseline technology adoption determine the subsequent periods technology adoption of male headed households. These differences are robust to model specifications and estimation strategies across the board.

5.4 Percentage marginal effects of Dynamic Technology Adoption

Using the results from Sections 5.1-5.3, we calculate the percentage marginal effects of technology adoption in order to investigate its cumulative effects categorized by Dynamic Probit, CLM Probit and gender of the household heads. We calculate these percentage marginal effects by dividing the marginal effects obtained in Model 4 (Tables 5-10) on lagged technology adoption and baseline technology adoption in Dynamic Probit and CML Probit models, respectively, and dividing them with the sample average technology adoption status. For example, for the Dynamic Probit estimation at the combined households level, the coefficient of lagged technology is 6.63% (Model 4, Table 5), which we divide 26%, the average technology adoption rate in our sample across the four waves. This method results in a cumulative marginal effect of 25%. Table 11 presents our calculations of the percentage marginal effects for dynamic technology adoption for combined and gender disaggregated households.

[Table 11 about here]

For the Dynamic Probit models, the percentage marginal effects represent the estimated effect of technology adoption in the previous period on the probability of adoption in the current period, as a percentage of sample average technology adoption rate. From the first column, we estimate that a household's technology adoption in the last period increases the cumulative likelihood of its technology adoption in the following period by 25%. Similarly, the second and third columns indicate that male and female households' technology adoption in the last period increase their cumulative likelihood of technology adoption in the following period by 17% and 61%, respectively. For the CML Probit models, the percentage marginal effects represent the estimated effect of technology adoption in the first period on the probability of adoption in the later periods, as a percentage of sample average technology adoption rate. From CML Probit in the first column, we estimate that a household's technology adoption in the baseline (i.e. 2005/06) increases the cumulative likelihood of its technology adoption in the subsequent periods by 19%. Similarly, the second column indicates that a male household's technology adoption in the baseline period increases its cumulative likelihood of technology adoption in the subsequent periods by 17%. The female household is left blank because baseline technology adoption is not significant for these households.

Our findings in Sections 5.1-5.4 show that baseline technology is the primary determinant of technology adoption at the aggregate household level of analysis. This conclusion is mainly driven by the male headed households who make 71% of the sample. As we saw in the descriptive analysis, male headed households have higher income and access to more farm plots. Therefore, male headed households are more likely to adopt in the baseline period and having reaped the benefits of investing in modern technology, they adhere to using modern technology in the subsequent periods. This is why for male headed households, technology adoption in the first period is the primary determinant of adoption in later periods, rather than the technology adoption in the immediate past. As for female headed households, they have lower income (medium to low levels) and access to fewer farm plots. Therefore, these households are less likely to adopt technology on average in the first period. Instead, they are more likely to move in and out of adoption status depending on their most recent experience with technology adoption such that lagged technology adoption is a more important determinant than baseline technology adoption. Finally, female households are the majority of the poorest households and they adopt less than male households. From this, we can infer that poorest households with very low endowments are so vulnerable that they never adopt and face lower returns. These findings broadly confirm those of Suri (2011) and Ma and Shi (2015) such that farmers learn from their past experiences and those with expected net benefits adopt, those with net expected loss do not adopt, and those with expected zero benefits move in and out of adoption status.

6. CONCLUSION AND POLICY IMPLICATIONS

Food insecurity is one of the leading causes of death in developing countries (WFP 2015). Moreover, SSA has the highest prevalence of food insecurity and is experiencing decreasing agricultural outputs over the last decade (Suri 2011). Therefore, low rates of technology adoption that cause inefficiencies in production in this region poses a natural question among development practitioners on what factors determine technology adoption. Furthermore, female farmers make up the majority of non-adopters, prompting a further analysis of gender issues in technology adoption. Recognizing the fact that technology adoption is a dynamic process, we empirically investigate the dynamics of technology adoption at combined and gender disaggregated household levels, using four waves of household level panel data from Uganda. By doing so, we contribute to the limited literature on empirical estimation of dynamics of technology. More specifically, our study is the first to estimate the dynamics of technology adoption decision by gender to the best of our knowledge.

Motivating our empirical analysis with a simple dynamic model of technology adoption and using several econometric techniques, we find that technology adoption in the first period is the primary determinant of technology adoption in the following periods. This finding is mainly driven by the male headed households who make the majority of the sample and have higher endowments. Female headed households are less likely to adopt technology in the first period and they have lower endowments. Technology adoption in the immediate past is the main driver of technology adoption in the current period for female headed households, such that they move in and out of adoption status depending on their most recent experience with technology adoption.

The results obtained in this study have important policy implications. Since technology adoption in the first period is the primary determinant of adoption in the subsequent years, this implies that policies should be in place to provide adequate training and complimentary environments before rolling out technology adoption so that barriers to adoption for marginal households in the first period are broken (e.g. female headed households). More specifically, female farmers and decision makers should be trained and informed about different varieties of modern technology and its benefits to farming. In addition, adult literacy programs should be catered towards female household heads. Finally, off-farm income sources should be made available to females, so that they can mitigate income shocks from farming. These facilities when made available would encourage the female headed households to adopt technology in the first period and continue adopting when they benefits from efficiencies of modern farming. The increased efficiency of the female farmers would also boost the agricultural productivity overall thus reducing the food insecurity of the region and the society as a whole. In future, studies should investigate adoption and disadoption patterns of technology, which will help pin the factors that cause this behavior.

TABLES AND FIGURES

Table 1: Dynamics of technology adoption for combined households

2005/06		2009/10		2010/11		2011/12	
0	**1283 (77%)**	**0**	**976 (76%)**	**0**	**857 (88%)**	**0**	**706 (82%)**
						1	151
				1	119	0	67
						1	52 (44%)
		1	307	0	175	0	111 (63%)
						1	64
				1	132 (43%)	0	64
						1	68 (52%)
1	**389 (23%)**	0	236	0	185 (78%)	0	149 (81%)
						1	36
				1	51	0	24
						1	27 (53%)
		1	**153 (39%)**	0	67	0	32 (48%)
						1	35
				1	**86 (56%)**	0	28
						1	**58 (67%)**

Note: 0 represents non-technology adoption status and 1 represents adopted. Percentages in parentheses represent percentages of households adopting or not adopting technology in a particular wave. With an exception of adopters in 2009/10, households that adopt (not adopt) technology in the first wave follow adoption (non-adoption) in the next wave.

Table 2: Summary statistics of households by wave and technology status

PANEL A

	2005-06			2009-10		
VARIABLES	Non-adopt	Adopt	P-value	Non-adopt	Adopt	P-value
Number of plots	5.71	8.35	***	6.05	7.35	***
Off-farm income/USh	148,707	161,363		410,272	488,164	
Farm income/USh	168,982	527,026	***	954,419	$1.14*10^{\wedge 6}$	***
Livestock value/USh	842,409	$1.04*10^{\wedge 6}$		$1.31*10^{\wedge 6}$	$1.67*10^{\wedge 6}$	
Prop. Of male heads (%)	71.55	81.23	***	68.65	81.09	***
Household size	5.78	7.01	***	6.50	7.39	***
HH head age/years	43.43	44.97	*	48.31	46.88	*
Total HH literacy	2.08	2.39	***	3.39	4.26	**
Extension visits	0.16	0.63	***	1.03	2.70	***
Participation in training	0.07	0.13	***	0.16	0.27	**
Weather shocks	0.37	0.35		0.20	0.20	
Other shocks	0.10	0.09		0.03	0.03	
Health shocks	0.09	0.11	*	0.08	0.08	
Number of households	389	1283		460	1212	

PANEL B

	2010-11			2011-12		
VARIABLES	Non-adopt	Adopt	P-value	Non-adopt	Adopt	P-value
Number of plots	6.59	7.42	***	5.82	6.43	***
Off-farm income/USh	557,831	843,073	*	657,742	$1.08*10^{\wedge 6}$	
Farm income/USh	641,140	$1.31*10^{\wedge 6}$	***	949,899	$1.90*10^{\wedge 6}$	***
Livestock value/USh	413,690	566,091	***	797,298	546,339	
Prop. male heads (%)	67.13	78.61	***	67.40	74.54	***
Household size	7.00	4.00	***	7.76	8.53	***
HH head age/years	48.78	47.80		49.77	48.48	*
Total HH literacy	3.80	4.60	***	4.45	5.58	***
Extension visits	0.65	1.70	***	0.81	1.21	**
Training program	0.17	0.25	**	0.19	0.35	*
Weather shocks	0.11	0.14	***	0.10	0.10	
Other shocks	0.01	0.01		0.01	0.01	
Health shocks	0.07	0.06		0.04	0.02	*
Number of households	388	1284		491	1181	

*** p<0.01, ** p<0.05, * p<0.1

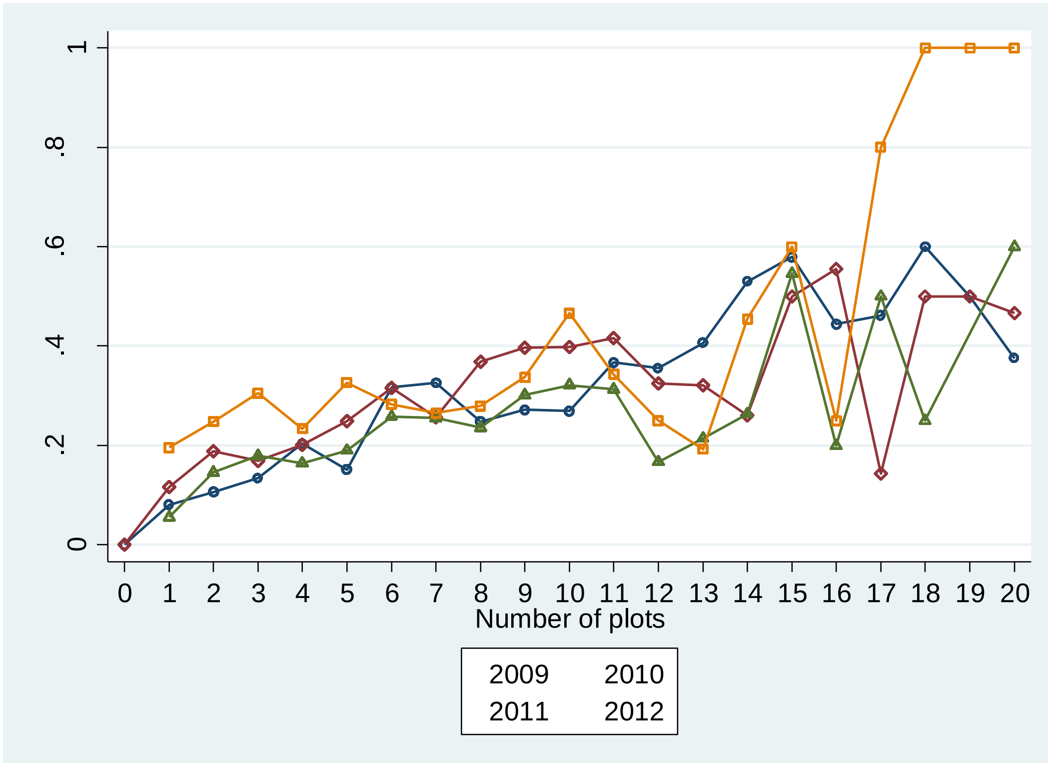

Figure 1: Fraction of households using technology versus number of plots

Table 3: Technology adoption by wave and gender

	2005-06		2009-10		2010-11		2011-12		Total	
Variables	Non-adopt	Adopt	Non-adopt	Adopt	Non-adopt	Adopt	Non-adopt	Adopt	Non-adopt	Adopt
Females	365	73	380	87	422	83	385	125	1552	368
Males	918	316	832	373	862	305	796	366	3408	1360
Total	1283	389	1212	460	1284	388	1181	491	4960	1728

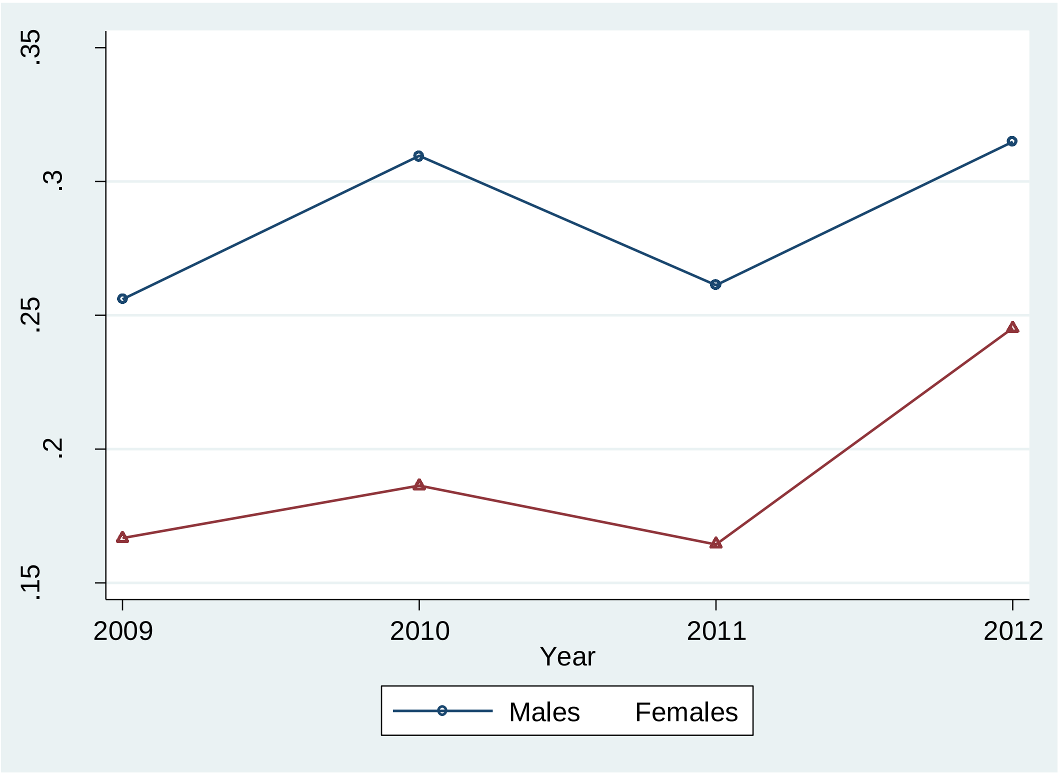

Figure 2: Fraction of households adopting technology by wave and gender

Table 4: Table 2: Summary statistics of households by wave and gender

	2005-06		2009-10		2010-11		2011-12	
VARIABLES	Female	Male	Female	Male	Female	Male	Female	Male
Technology	0.17	0.26***	0.19	0.31***	0.16	0.26***	0.25	0.31***
Number of plots	5.69	6.55***	5.81	6.64***	6.31	6.99***	5.52	6.21***
Off-farm income/USh	152,512	151,347	262,091	497,435**	409,483	716,863*	744,884	797,238
Farm income/USh	96,086	307,724***	981,666	1.02*10^6	504,663	923,196***	683,682	1.47*10^6***
Livestock value/USh	585,054	998,962*	1.21*10^6	1.484e+06	325,350	502,441***	440,929	847,659
Household size	5.34	6.29***	5.63	7.11***	7.80	8.23	6.94	8.21***
HH head age/years	47.80	42.37***	52.16	46.27***	51.77	47.16***	52.78	47.90***
Total HH literacy	1.65	2.32***	2.92	3.80***	3.50	4.03***	4.04	4.75***
Extension visits	0.25	0.28	0.88	1.72***	0.54	1.05***	0.63	1.06**
Training program	0.06	0.09**	0.13	0.21***	0.14	0.22***	0.18	0.27***
Weather shocks	0.36	0.37	0.21	0.19**	0.11	0.13*	0.10	0.10
Other shocks	0.10	0.09	0.03	0.03	0.01	0.01	0.01	0.01**
Health shocks	0.12	0.09***	0.10	0.07**	0.08	0.06*	0.04	0.03**
Number of households	438	1234	467	1205	505	1167	510	1162

The *s in male column represent the p-value significance of the difference in mean comparison between male and female headed households, where *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Marginal effects from Dynamic Probit of the technology adoption

VARIABLES	(1)	(2)	(3)	(4)
Lagged technology	0.0935***	0.0729***	0.0907***	0.0653***
	(0.0215)	(0.0199)	(0.0223)	(0.0208)
Number of plots	0.0108***	0.0166***	-0.0024	0.0025
	(0.0022)	(0.0021)	(0.0020)	(0.0019)
Ln off-farm income/USh	0.0040**	0.0040***	0.0016	0.0014
	(0.0015)	(0.0015)	(0.0013)	(0.0013)
Ln farm income/USh	0.0050***	0.0042***	0.0076***	0.0071***
	(0.0013)	(0.0012)	(0.0012)	(0.0012)
Ln livestock value /USh	0.0036***	0.0043***	0.0016	0.0000
	(0.0011)	(0.0013)	(0.0014)	(0.0014)
HH head sex	0.0495***	0.0628***	0.0585***	0.0715***
	(0.0174)	(0.0162)	(0.0174)	(0.0165)
Household size	0.0080***	-0.0006	0.0070***	0.0018
	(0.0016)	(0.0023)	(0.0015)	(0.0029)
HH head age	-0.0013**	-0.0014***	-0.0012**	-0.0014***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Total HH literacy	0.0100***	0.0118***	0.0124***	0.0141***
	(0.0026)	(0.0024)	(0.0026)	(0.0027)
Extension visits	0.0024	0.0023*	0.0028*	0.0028*
	(0.0015)	(0.0014)	(0.0015)	(0.0014)
Training program	0.0686***	0.0702***	0.0703***	0.0775***
	(0.0167)	(0.0160)	(0.0168)	(0.0162)
Weather shocks	0.0074	-0.0360	0.0198	-0.0323
	(0.0382)	(0.0374)	(0.0381)	(0.0378)
Other shocks	-0.0719	-0.2030*	-0.0575	-0.1900
	(0.1250)	(0.1210)	(0.1260)	(0.1220)
Health shocks	-0.0284	-0.0221	-0.0343	-0.0317
	(0.0404)	(0.0388)	(0.0406)	(0.0394)
Log likelihood	-2622***	-2493***	-2633***	-2521***
Region Dummy	No	Yes	No	Yes
Year Dummy	No	Yes	No	Yes
Observations	5,016	5,016	5,016	5,016
Number of HHID	1,672	1,672	1,672	1,672

Notes: (i) Standard errors in parentheses. (ii) *** p<0.01, ** p<0.05, * p<0.1. (iii) Model 1 assumes no endogeneous regressors; Model 2 adds region and year dummies; Model 3 uses lagged incomes; Model 4 adds region and year dummies to Model 3.

Table 6: Marginal effects from CML Probit of the technology adoption

VARIABLES	(1)	(2)	(3)	(4)
Lagged technology	0.0387*	0.0377*	0.0318	0.0252
	(0.0220)	(0.0212)	(0.0224)	(0.0217)
Baseline Technology	0.0906***	0.0415**	0.0934***	0.0496**
	(0.0209)	(0.0193)	(0.0210)	(0.0197)
Number of plots	0.0105***	0.0155***	-0.0029	0.0015
	(0.0022)	(0.0021)	(0.0020)	(0.0020)
Ln off-farm income/USh	0.0042***	0.00401***	0.0015	0.0014
	(0.0016)	(0.0015)	(0.0013)	(0.0013)
Ln farm income/USh	0.00466***	0.0042***	0.0072***	0.0071***
	(0.0013)	(0.0012)	(0.0012)	(0.0012)
Ln livestock value /USh	0.0033***	0.0042***	0.0005	-0.0010
	(0.0011)	(0.0013)	(0.0015)	(0.0014)
HH head sex	0.0699	0.0828*	0.0759	0.0843*
	(0.0463)	(0.0446)	(0.0462)	(0.0450)
Household size	0.0089***	0.00162	0.0074***	0.0022
	(0.0016)	(0.0036)	(0.0016)	(0.0036)
HH head age	-0.0013	-0.0029	-0.0016	-0.0027
	(0.0020)	(0.0020)	(0.0020)	(0.0020)
Total HH literacy	0.0071*	0.0045	0.0072*	0.0056
	(0.0039)	(0.0039)	(0.0040)	(0.0040)
Extension visits	-0.0014	-0.0010	-0.0013	-0.0011
	(0.0017)	(0.0016)	(0.0017)	(0.0016)
Training program	0.0345*	0.0267	0.0299	0.0258
	(0.0197)	(0.0194)	(0.0198)	(0.0195)
Weather shocks	-0.0120	-0.0269	-0.0073	-0.0320
	(0.0409)	(0.0406)	(0.0409)	(0.0410)
Other shocks	-0.0982	-0.111	-0.0733	-0.0932
	(0.128)	(0.124)	(0.129)	(0.126)
Health shocks	0.0152	0.0232	0.0061	0.0120
	(0.0443)	(0.0432)	(0.0444)	(0.0436)
Log likelihood	-2594***	-2466***	-2602***	-2490***
Region dummy	No	Yes	No	Yes
Year dummy	No	Yes	No	Yes
Mean of exogeneous variables	Yes	Yes	Yes	Yes
Observations	5,016	5,016	5,016	5,016
Number of HHID	1,672	1,672	1,672	1,672

Notes: (i) Standard errors in parentheses. (ii) *** p<0.01, ** p<0.05, * p<0.1. (iii) Model 1 assumes no endogeneous regressors; Model 2 adds region and year dummies; Model 3 uses lagged incomes; Model 4 adds region and year dummies to Model 3.

Table 7: Technology adoption marginal effects from Dynamic Probit for male households

VARIABLES	(1)	(2)	(3)	(4)
Lagged technology	0.0851***	0.0616***	0.0788***	0.0495*
	(0.0261)	(0.0239)	(0.0276)	(0.0255)
Number of plots	0.0133***	0.0195***	-0.0018	0.0038
	(0.00269)	(0.0026)	(0.0025)	(0.0024)
Ln off-farm income/USh	0.00242	0.0028	0.0015	0.0009
	(0.0020)	(0.0019)	(0.0017)	(0.0017)
Ln farm income/USh	0.0039**	0.0031*	0.0074***	0.0066***
	(0.0017)	(0.0016)	(0.0016)	(0.0015)
Ln livestock value /USh	0.0053***	0.0059***	0.0034*	0.0015
	(0.0014)	(0.0016)	(0.0019)	(0.0018)
Household size	0.0085***	-0.0007	0.0071***	0.0022
	(0.0019)	(0.0036)	(0.0019)	(0.0037)
HH head age	-0.0016**	-0.0018***	-0.0014**	-0.0016**
	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Total HH literacy	0.0100***	0.0117***	0.0123***	0.0143***
	(0.0034)	(0.0033)	(0.0034)	(0.0034)
Extension visits	0.0024	0.0026*	0.0029*	0.0027*
	(0.0017)	(0.0016)	(0.0017)	(0.0016)
Training program	0.0717***	0.0721***	0.0720***	0.0796***
	(0.0207)	(0.0197)	(0.0209)	(0.0200)
Weather shocks	0.0038	-0.0421	0.0202	-0.0411
	(0.0488)	(0.0471)	(0.0489)	(0.0481)
Other shocks	-0.0386	-0.190	-0.0163	-0.180
	(0.157)	(0.149)	(0.158)	(0.152)
Health shocks	-0.0351	-0.0304	-0.0309	-0.0361
	(0.0537)	(0.0511)	(0.0540)	(0.0521)
Log likelihood	-9438***	-1838***	-1951***	-1866***
Region dummy	No	Yes	No	Yes
Year dummy	No	Yes	No	Yes
Observations	3,534	3,534	3,534	3,534
Number of HHID	1,232	1,232	1,232	1,232

Notes: (i) Standard errors in parentheses. (ii) *** p<0.01, ** p<0.05, * p<0.1. (iii) Model 1 assumes no endogeneous regressors; Model 2 adds region and year dummies; Model 3 uses lagged incomes; Model 4 adds region and year dummies to Model 3.

Table 8: Technology adoption marginal effects from CML Probit for male headed households

VARIABLES	(1)	(2)	(3)	(1)
Lagged technology	0.0304	0.0300	0.0176	0.0136
	(0.0270)	(0.026)	(0.0276)	(0.0264)
Baseline Technology	0.0936***	0.0346	0.1020***	0.0467*
	(0.0267)	(0.0243)	(0.0269)	(0.0250)
Number of plots	0.0128***	0.0183***	-0.0024	0.00274
	(0.0027)	(0.0026)	(0.0025)	(0.0024)
Ln off-farm income/USh	0.00287	0.0030	0.0018	0.0010
	(0.0020)	(0.0019)	(0.0017)	(0.0017)
Ln farm income/USh	0.0035**	0.0030*	0.0071***	0.0064***
	(0.0017)	(0.0016)	(0.0016)	(0.0015)
Ln value of livestock/USh	0.0050***	0.0056***	0.00215	0.0006
	(0.0014)	(0.0016)	(0.0019)	(0.0018)
Household size	0.0093***	0.0009	0.0076***	0.0027
	(0.0020)	(0.0045)	(0.0020)	(0.0046)
HH head age	-0.0006	-0.0027	0.0044	-0.0024
	(0.0032)	(0.0030)	(0.0042)	(0.0031)
Total HH literacy	0.0065	0.0039	0.0054	0.0059
	(0.0050)	(0.0049)	(0.0050)	(0.0049)
Extension visits	-0.0013	-0.0010	-0.0009	-0.0011
	(0.0019)	(0.0018)	(0.0019)	(0.0018)
Training program	0.0446*	0.0367	0.0381	0.0371
	(0.0242)	(0.0235)	(0.0245)	(0.0238)
Weather shocks	-0.0154	-0.0378	-0.0021	-0.0419
	(0.0520)	(0.0509)	(0.0526)	(0.0517)
Other shocks	-0.0623	-0.0913	-0.0242	-0.0720
	(0.160)	(0.154)	(0.162)	(0.156)
Health shocks	0.0093	0.0149	0.0261	0.0107
	(0.0579)	(0.0560)	(0.0588)	(0.0568)
Log likelihood	-1919***	-1821***	-1927***	-1845***
Region dummy	No	Yes	No	Yes
Year dummy	No	Yes	No	Yes
Mean of exogeneous variables	Yes	Yes	Yes	Yes
Observations	3,534	3,534	3,534	3,534
Number of HHID	1,232	1,232	1,232	1,232

Notes: (i) Standard errors in parentheses. (ii) *** p<0.01, ** p<0.05, * p<0.1. (iii) Model 1 assumes no endogeneous regressors; Model 2 adds region and year dummies; Model 3 uses lagged incomes; Model 4 adds region and year dummies to Model 3.

Table 9: Marginal effects from Dynamic Probit of the technology adoption for male headed households

VARIABLES	(1)	(2)	(3)	(4)
Lagged technology	0.1450***	0.1310***	0.1290***	0.1150***
	(0.0337)	(0.0322)	(0.0347)	(0.0339)
Number of plots	0.0047	0.00960***	-0.0048	-0.0010
	(0.0035)	(0.00348)	(0.0032)	(0.0032)
Ln off-farm income/USh	0.0069***	0.00624***	0.0028	0.0028
	(0.0023)	(0.00225)	(0.0021)	(0.0021)
Ln farm income/USh	0.0078***	0.00720***	0.0087***	0.0086***
	(0.0019)	(0.00187)	(0.0019)	(0.0019)
Ln value of livestock/USh	-0.0002	0.000222	-0.0014	-0.0024
	(0.0017)	(0.00194)	(0.0020)	(0.0020)
Household size	0.0067**	-0.00140	0.0067**	0.0000
	(0.0027)	(0.00455)	(0.0027)	(0.0046)
HH head age	-0.0005	-0.000566	-0.0006	-0.0007
	(0.0007)	(0.000703)	(0.0007)	(0.0007)
Total HH literacy	0.0108***	0.0130***	0.0128***	0.0145***
	(0.0039)	(0.00417)	(0.0040)	(0.0042)
Extension visits	0.0038	0.00428	0.0030	0.0038
	(0.0039)	(0.00376)	(0.0039)	(0.0038)
Training program	0.0650**	0.0690**	0.0731**	0.0782***
	(0.0293)	(0.0287)	(0.0294)	(0.0288)
Weather shocks	0.0063	-0.0316	0.0142	-0.0178
	(0.0590)	(0.0591)	(0.0590)	(0.0594)
Other shocks	-0.113	-0.206	-0.155	-0.210
	(0.211)	(0.206)	(0.215)	(0.211)
Health shocks	-0.0146	-0.00216	-0.0414	-0.0232
	(0.0571)	(0.0556)	(0.0577)	(0.0564)
Log likelihood	-677***	-645***	-676***	-647***
Region dummy	No	Yes	No	Yes
Year Dummy	No	Yes	No	Yes
Observations	1,482	1,482	1,482	1,482
Number of HHID	547	547	547	547

Notes: (i) Standard errors in parentheses. (ii) *** p<0.01, ** p<0.05, * p<0.1. (iii) Model 1 assumes no endogeneous regressors; Model 2 adds region and year dummies; Model 3 uses lagged incomes; Model 4 adds region and year dummies to Model 3.

Table 10: Marginal effects from CML Probit of the technology adoption for male headed households

VARIABLES	(1)	(2)	(3)	(4)
Lagged technology	0.1040***	0.0982***	0.0787**	0.0705*
	(0.0381)	(0.0368)	(0.0388)	(0.0381)
Baseline Technology	0.0605*	0.0364	0.0675**	0.0465
	(0.0311)	(0.0295)	(0.0315)	(0.0302)
Number of plots	0.0044	0.0089**	-0.0054*	-0.0019
	(0.0036)	(0.0035)	(0.0033)	(0.0033)
Ln off-farm income/USh	0.0066***	0.0062***	0.0025	0.0027
	(0.0023)	(0.0023)	(0.0021)	(0.0021)
Ln farm income/USh	0.0075***	0.0072***	0.0087***	0.0089***
	(0.0019)	(0.0019)	(0.0019)	(0.0019)
Ln value of livestock/USh	-0.0001	0.0007	-0.0020	-0.0030
	(0.0018)	(0.0020)	(0.0021)	(0.0020)
Household size	0.0072**	-0.0008	0.0067**	-0.0016
	(0.0030)	(0.0058)	(0.0029)	(0.0058)
HH head age	-0.0025	-0.0040	-0.0017	-0.0034
	(0.0031)	(0.0032)	(0.0031)	(0.0032)
Total HH literacy	0.0143**	0.0132*	0.0132*	0.0114*
	(0.00688)	(0.0070)	(0.0068)	(0.0069)
Extension visits	-0.0028	-0.0012	-0.0053	-0.0038
	(0.0051)	(0.0050)	(0.0050)	(0.0049)
Training program	0.0197	0.0113	0.0195	0.0116
	(0.0380)	(0.0377)	(0.0378)	(0.0376)
Weather shocks	-0.0116	-0.0124	-0.0196	-0.0158
	(0.0672)	(0.0687)	(0.0668)	(0.0684)
Other shocks	-0.0914	-0.0932	-0.148	-0.123
	(0.219)	(0.216)	(0.222)	(0.221)
Health shocks	0.0852	0.101	0.0389	0.0613
	(0.0706)	(0.0694)	(0.0710)	(0.0700)
Log likelihood	-667***	-635***	-666***	-635***
Region dummy	No	Yes	No	Yes
Year dummy	No	Yes	No	Yes
Mean of exogeneous variables	Yes	Yes	Yes	Yes
Observations	1,482	1,482	1,482	1,482
Number of HHID	547	547	547	547

Notes: (i) Standard errors in parentheses. (ii) *** p<0.01, ** p<0.05, * p<0.1. (iii) Model 1 assumes no endogeneous regressors; Model 2 adds region and year dummies; Model 3 uses lagged incomes; Model 4 adds region and year dummies to Model 3.

Table 11: Percentage marginal effects of Dynamic Technology Adoption by Gender and Methodology

Estimation Models	Combined Households	Male Headed Households	Female Headed Households
Dynamic Probit	25.11***	17.10*	60.53***lagged
CML Probit	19.08**	16.10*	---
Sample average adoption rate	26.00	29.00	19.00

Notes: For the Dynamic Probit models, the percentage marginal effects represent the estimated effect of technology adoption in the previous period on the probability of adoption in the current period, as a percentage of sample average technology adoption rate. For the CML Probit models, the percentage marginal effects represent the estimated effect of technology adoption in the first period on the probability of adoption in the later periods, as a percentage of sample average technology adoption rate. All effects are calculated for Model 4 of Tables 5-10. The CML Probit percentage marginal effects for female headed households are left blank because the baseline technology adoption is not significant for these households. *** p<0.01, ** p<0.05, * p<0.1.

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