Drought Experience, Risk Preferences and Adoption of Improved Production Technologies among Smallholder Farmers in Ghana

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Abstract

We investigate maize variety selection and fertilizer application practices among food insecure smallholder farmers in drought-prone Northern Ghana. Field experiments were conducted to elicit risk preferences that allow for risk aversion and subjective probability weighting. Experimental observations were combined with detailed household information including recent experiences with drought, aspirations, landholdings, experience growing maize, non-agricultural income, credit and saving, social networks, and drought adaptation and mitigation strategies. Our findings help explain delayed and low take up of new improved agricultural technologies in Ghana: Farmers who exhibit greater risk aversion are more likely to grow local maize and less likely to grow improved high yield maize. Overweighting of low probabilities is associated with low application of inorganic compounds and inorganic straight fertilizer to both local and high yield maize. High aspirations are associated with greater adoption of high yield maize. Peer consultation increases adoption of high yield maize and application of inorganic fertilizer. Experience with past droughts discourages adoption of improved high yield maize.

Key words: Technology adoption, risk aversion, subjective probability weighting, aspiration index.

1. Introduction

Adoption of new agricultural production technologies in developing countries has attracted considerable attention because of their high dependence on primary agricultural production and growing concerns over climate change and rising weather variability (Feder, Just, & Zilberman, 1985). New agricultural technologies promise to increase agricultural production and income and to reduce poverty. However, new agricultural technologies have not exhibited the hoped-for take up in developing countries. Given this, there is a need to better understand agricultural household technology adoption decisions in developing countries.

Impediments to the adoption of improved agricultural technologies in developing countries include lack of access to credit and saving facilities, limited access to information, lack of water resources, small farm sizes, inadequate farm tenure incentives, insufficient human capital, absence of capital equipment, erratic availability of complementary inputs (such as seed and fertilizer), and inadequate transportation infrastructure. Risk presents yet another impediment to the adoption of innovative technologies, given that these technologies can raise expected production, but can also increase yield variability and probabilities of crop failure (Yesuf & Bluffstone, 2009).

Many interventions have sought to alleviate constraints to adoption of new agricultural technologies by improving financial access, creating incentives to saving, offering insurance to cover downside risks, improving the quality public information, increased investment in infrastructure, and promotion of marketing networks (Fafchamps, Udry, & Czukas, 1998; Miranda & Gonzalez-Vega, 2010). However, immediate and uniform adoption of improved agricultural technologies is still quite rare with some evidence of dis-adoption.

Few studies have looked at risk preferences and belief as determinants of agricultural technology adoption decisions in developing countries, and those that do generally employ an Expected Utility risk preference framework. Examples include: Srinivasan (1972), one of the first studies to look at technology adoption under uncertainty in developing countries. He finds that farmers' risk attitudes provide an alternate explanation for the decline in agricultural productivity in India. Feder (1980) assesses risk aversion among farmers who grow both modern and traditional crops using a stochastic production function approach. He finds that fertilizer use is independent of risk aversion if farmers are not credit constrained. Knight, Weir, and Woldehanna (2003) find that risk averse farmers in Ethiopia adopt new technologies at a lower rate than risk-neutral farmers. Hill (2009) uses stated preference and beliefs to assess the effects of risk aversion on production decisions and finds that greater risk aversion is directly correlated with the reduction of labor among coffee growers in Uganda. Wossen, Berger, and Di Falco (2015) find that famers' social capital plays a significant role in the adoption of improved farmland management practices in Ethiopia, with an affect that varies with farmers' risk preferences. Ahsanuzzaman and George (2016) conducted an experiment to investigate how peer group consultation affects farmer's attitudes toward uncertainty (risk and ambiguity) and their technology adoption decisions. They find that neither risk aversion nor ambiguity aversion matter when farmers face uncertainty in groups of six. On the contrary, farmers who interact with others appear to strategically delay adoption to free-ride on the experiences gathered by others. In a study of adoption decisions and social networking in Mozambique, Bandiera and Rasul (2006) find that the relationship between the probability of adoption and the number of known adopters exhibits an inverse-U shape. These studies mostly find that farmers exhibiting greater risk aversion are less likely to adopt new technologies.

However, recent studies have extend the Expected Utility framework to consider subjective belief in technology adoption. Liu (2013), Liu and Huang (2013) and Holden (2015) appear to be the first to employ Prospect Theoretic nonlinear probability weighting in household technology adoption decisions. Liu (2013), finds that farmers who are more risk averse adopt new technology later and farmers who overweigh small probabilities adopt it earlier. In a similar study, Liu and Huang (2013) find that pesticide use among cotton farmers in China is positively correlated with risk aversion but negatively correlated with loss aversion. Following the same line of analysis, Holden (2015) conducts a field experiment to assess how well Prospect Theory explains the adoption and use of new technologies among food insecure farmers in Malawi. The author finds that farmers with higher risk aversion are more likely to adopt Drought Tolerant maize, less likely to adopt improved maize and less likely to dis-adopt traditional local maize. The author also finds that recent experience with drought increases the likelihood of Drought Tolerant maize adoption and over-weighting of small probabilities leads to reduced fertilizer use.

There is also a new growing literature on the role of aspirations in investment decisions in developing countries. Bernard et al. (2014) conduct a Randomized Controlled trials experiment to test the effect of aspiration on investment in Ethiopia. The experiment consists of: Firstly, individuals were randomly invited to watch documentaries about people from similar communities who had succeeded in agriculture or small business, without help from government or NGOs. A placebo group watched an Ethiopian entertainment program and a control group were simply surveyed. Secondly, the number of invitees was varied by village to assess the importance of peer effects on the formation of aspirations. The authors find that aspirations heightened among treated farmers, but not among those in the placebo or control groups. They also find evidence of treatment effects on savings and credit behavior and investment in children's schooling. This suggests that change in aspirations can translate into changes in saving, credit and adoption behavior.

The objective of this study is to employ Prospect Theory framework to assess how risk preferences (risk aversion and subjective probability weight), experiences with drought, aspirations, and peer consultation affect the adoption and usage of high yield maize and fertilizer types in Northern Ghana. We conduct a field experiment to elicit risk aversion and subjective probability weight parameters of farmers and correlate our observations to detailed household survey data on adoption and usage of different maize varieties, fertilizer use, aspiration indices, food insecurity, recent experiences with drought, farm size and farmer socio-economic characteristics including gender, marital status, age and education of the head of household.

2. Context of the Experiment and Data Collection

2.1. Context of the Experiment

In this study, we use the Holt and Laury (2002) experimental approach to uncover risk aversion and subjective probability weighting parameters among smallholders in Northern Ghana. The experiment was conducted as part of an ongoing impact evaluation study of the effects of index insurance-backed contingent credit on production technology adoption among smallholders in Ghana. The study, which is funded by the US Agency for International Development, is a three-year randomized controlled trial (RCT) that began in January 2014 in Northern Ghana. The study, which is being conducted in collaboration with 14 Rural and Community Banks (RCBs) and the Ghana Agricultural Insurance Pool, offered index-insured loans to 279 randomly-selected smallholder lending groups, comprising 89 groups from five districts of Northern region, 33 groups from six districts of the Upper West region, and 157 groups from ten districts of the Upper East region[1].

In order to elicit farmers' risk aversion and subjective probability weighting parameters, we interviewed a random subsample of 333 farmers included in the RCT: 57 farmers from 16 communities in Bawku West district, 42 farmers from 7 communities in Bawku Municipal district, 42 farmers from 7 communities in Binduri district, and 192 farmers from 36 communities in Garu Tempane district. Farmers selected for the risk elicitation study experiment were contacted by local extension workers and given the option to participate. We conducted one training session for ten enumerators, six Ghana Ministry of Food and Agriculture extension specialists and four national services personnel from the Tamale University of Development Studies. We then conducted five training sessions for farmers, one in Bawku East, one in Bawku West, one in Binduri, and two in Garu Tempane. Two farmers were dropped for failing to complete the training sessions.

Enumerators initiated the experiment two days after training. Because the farmers in our experiments were already participating in the general baseline survey, we had data regarding farmer household demographic and socio-economic characteristics, including agricultural production practices, landholdings, experience growing maize, non-agricultural income, credit and saving, drought perceptions, social networks, drought adaptation and mitigation strategies.

2.2. Experimental Design

The experiment to elicit risk preferences is framed around the adoption of high yield but risky variety of maize (HYV) and consisted of offering a menu of ordered lottery choices over hypothetical gains to the farmers. The first option (the safer option, option A) provides traditional maize that yields 350 kg of maize per hectare with good rains, but yields a slightly lower 250 kg

[1] The lending groups participating in the study were selected randomly from 791 groups serviced by lenders in the Association of Rural Banks – Northern Chapter. Selection was based on five criteria: 1- Farmer groups that have been in good standing with the bank in terms of borrowing, potential groups that are qualified to receive loans and groups that have been denied loan due to low regional rainfall; 2- Farmers that belong to districts that belong to low rainfall areas (between 800-1100mm annually) since the impact of insured loan is more likely to be seen when rainfall is low; 3- Farmer groups whose primary or secondary crop is maize since maize is the primary crop grown in the northern regions; 4- Farmers groups with 7-15 members due to budget constraints and logistics of maintaining smoother field work; 5- Farmers that take out a loan of less than 10,000 GHC because farmers above this range are outliers and are beyond the definition of smallholder farmers.

of maize per hectare with bad rains. The second option (the risky option, option B) provides “high yield” maize (HYV) that yields 750 kg of maize per hectare with good rains, but only 50 kg of maize per hectare with bad rains. Farmers were asked to choose between these two options under 10 different scenarios in which the probability of good rains was gradually increased from 10 percent to 100 percent[2].

The payoff matrix for the experimental lottery is presented in Table 1. Each row of the table represents a situation in which farmers were asked to choose between the safer option (A) and the riskier option (B) assuming a particular probability of good rains. The net expected value of each choice (not shown to the respondent) is computed as:

$$E(A)-E(B)=\sum_{s=1}^{2} p(A_s)A_s-\sum_{s=1}^{2} p(B_s)B_s$$

where for each option (A or B), s = 1 good rains, and s = 2 poor rains. As shown in Table 1, the expected yield was always higher for option B than option A for probabilities of good rains of 40 percent and above. Using Prospect Theory, we estimated a Rank-Dependent Utility Model with Power Risk Utility Function that embeds Expected Utility Theory and constant relative risk aversion as independent special cases characterized by specific parametric restrictions. We jointly estimated individual utility of money function and subjective probability weighting function parameters.

Table 1: Payoff matrix, hypothetical experiment.

Variety A				Variety B				E(A)	E(B)	E(A)-E(B)
$P(A_1)$	A_1	$P(A_2)$	A_2	$P(B_1)$	B_1	$P(B_2)$	B_2			
0.1	350	0.9	250	0.1	750	0.9	50	260	120	140
0.2	350	0.8	250	0.2	750	0.8	50	270	190	80
0.3	350	0.7	250	0.3	750	0.7	50	280	260	20
0.4	350	0.6	250	0.4	750	0.6	50	290	330	-40
0.5	350	0.5	250	0.5	750	0.5	50	300	400	-50
0.6	350	0.4	250	0.6	750	0.4	50	310	470	-160
0.7	350	0.3	250	0.7	750	0.3	50	320	540	-220
0.8	350	0.2	250	0.8	750	0.2	50	330	610	-280
0.9	350	0.1	250	0.9	750	0.1	50	340	680	-340
1.0	350	0.0	250	1.0	750	0.0	50	350	750	-400

[2] Note that in this context risk preferences are being asked in a narrow, hypothetical context, and that farmers' previous experience with actual rainfall might affect the subjective beliefs that farmers have about rainfall in the experiment (de Brauw & Eozenou, 2014).

2.3.Drought Experience and Technology Adoption

Rainfall risk is the dominant risk in rain-fed crop production. We pay particular attention to past experiences with drought as described by the farmers themselves. In particular, we asked the farmers to recall whether they experienced drought that affected their crops in the preceding growing season and the number of times they experienced drought over the past five growing seasons. As in most studies, farmers had no difficulties recalling drought events and their answers were consistent across farms in given neighborhoods. We therefore used these two variables as indicators of drought experience.

Perception of drought risk can also affect farmer's willingness to adopt high yield but risky technology. In our household survey, we asked farmers: "*In your view what is the likelihood that there will be drought next growing season*", we thought farmers who strongly believe that there will be drought next season can be skeptical about risky technologies even though highly productive.

2.4. Aspirations and Technology Adoption

The impact of aspirations on future-oriented behavior has received increased attention in the development economics literature in recent years. The word "aspiration" means "a desire or ambition to achieve something" (Oxford English Dictionary, 1989). The word signifies some goal and a desire to attain it.

We use the survey data to construct specific measures of aspirations in four dimensions: income, wealth, social status and children's educational attainment. For each of these dimensions, respondents were asked "*what level on this dimension they would like to achieve*". The survey instrument's validity and reliability was tested in 2009 in 16 villages in central Ethiopia by Bernard et al. (2014).

In this study, income aspirations, measured in Ghana cedi, includes cash income from all activities. Wealth aspirations included housing, vehicles, furniture and other valuable durables. Educational aspirations are measured by the highest level of education the respondent want their eldest child to achieve. Social status aspirations are measured by the percentage of community members who would ask for the respondent's advice at times of important decisions. The aspiration index was computed for respondent *i* using equation (1):

$$A_i = \sum_k w_i^k \left(\frac{a_i^k - u^k}{\sigma^k} \right) \tag{1}$$

where a_i^k denotes the individual's aspiration for dimension k, w_i^k is the weight the individual assigns to this dimension, u^k and σ^k measure the sample mean and standard deviation of aspirations of dimension k.

3. Data Description

Table 2 presents descriptive statistics for the sample observations. The average relative risk aversion coefficient of farmers, 0.790, is comparable to that found among smallholder farmers by Binswanger (1980) in India,. The average subjective probability weight is 0.951, indicating that farmers overweight small probabilities and underweight large probabilities relative to the objective probabilities. Similar result is found in Kahneman and Tversky (1979) paper. A typical household in Northern Ghana holds livestock, including chickens, bulls, cows, sheep and goats. Livestock are significant assets sold to finance consumption needs especially during drought periods. Most farmers in our sample have at least one livestock. The average livestock endowment measured in terms of tropical livestock unit (TLU) is 5.59 compared to 1.2 in Uganda (Tatwangire, 2011) and 4.0 in Kenya (Onduru & Du Preez, 2007). Women are mostly smallholder farmers. Indeed, 60 percent of our sample are female. More than 80 percent of farmers in our sample have never attended school and fewer than seven percent had attended at least middle school. Food insecurity was a big challenge for many households, more than 42 percent of our sample were severe food insecure with only 16 percent food secure.

The average aspiration index of farmers was very low in our sample (0.012) compared to the one found in Bernard et al. (2014) study in Ethiopia (0.03).

Table 2: List of Variables

Variable	Obs	Mean	Std. Dev
Relative Risk Aversion	331	0.790	0.082
Subjective Probability Weight	331	0.951	0.318
Aspiration Index	331	0.012	0.570
Peers Consultation	331	4.933	2.364
Drought 2014, Dummy	331	0.637	0.481
Number of Drought, Previous 5 Seasons	331	2.519	0.832
Medical Emergencies in Household	331	0.323	0.468
Death of Household Member	331	0.148	0.355
Farm Size (Acres)	331	5.939	4.144
Distance to Nearest Market (Minutes)	331	64.283	47.661
Food Security Status[3]			
Moderate Food Insecure	331	0.251	0.434
Middle Food Insecure	331	0.169	0.375
Severe Food Insecure	331	0.420	0.494
Sex of Household Head (1. Male, 0. Female)	331	0.404	0.491
Age of Household Head	331	46.809	13.473
Level of Education			
Primary	331	.0392	.194
Middle Schools	331	.039	.194
High Schools/SSS/Secondary	331	.027	.162
College/University	331	.015	.122
Dependency Ratio	331	1.145	0.896
Household Savings (100 GHS)	331	2.963	4.109
Household Loan received (100 GHS)	331	2.787	2.240
Livestock Endowment (TLU)	331	5.586	15.993
Improved Maize Seed Variety, Dummy	331	0.129	0.336
Local Maize, Dummy	331	0.845	0.362
Improved Maize Seed Variety Planted (kg)	331	2.453	16.141
Local Maize Planted (kg)	331	4.572	5.336
Organic Fertilizer Use Improved Maize Variety (1000kg)	331	1.762	11.829
Inorganic Compound Fertilizer Use Improved Maize (kg)	331	31.419	160.096
Inorganic Straight Fertilizer Use Improved Maize Variety (kg)	331	17.975	86.874
Organic Fertilizer Use on Local Maize (1000kg)	331	62.198	130.288
Inorganic Compound Fertilizer Use on Local Maize (kg)	331	132.40	175.922
Inorganic Straight Fertilizer Use on Local Maize (kg)	331	80.830	104.828

[3] There is a new direction in measuring food insecurity based on people's access to quantity and quality food. This method is derived from the US Household Food Security Survey Module (HFSSM) and the Latin American and Caribbean Food Security Scale and it is being used worldwide by the FAO Voices of the Hungry (VOH) project in the form of Food Insecurity Experience scale (FIES). The FIES questions ask people directly about having to compromise the quality and quantity of the food they eat due to limited money or other resources to obtain food. It is composed of 8 items, each item refers to a different situation and is associated with a level of severity according to the theoretical construct of food insecurity underlying the scale. The analysis of the FIES is based on the Item Response Theory (IRT) commonly used in the educational and psychological tests. Among the models based on the IRT, the VoH uses the One Parameter Logistics Model (*Rasch Model*), which represents the probability that an individual with food insecurity b_h responds positively to an item characterized by severity level a_i is modelled as a logistic function of the distance between *bh* and *ai*: $\Pr ob(x_{h,i} = 1 \mid b_h, a_i) = F(b_h - a_i) = \frac{e^{b_h - a_i}}{1 + e^{b_h - a_i}}$,(Rash, 1960) . Note: Food security status is measured in a scale of 1 to 4 with 1=food secure, 4=severe food insecure.

Drought is a major concern for farmers in our sample, as few have access to irrigation. More than 36 percent of farmers in our sample experienced drought the previous growing season, more than 90 percent had experienced at least one drought over the preceding five growing seasons, and more than 60 percent had experienced at least three droughts over the preceding five seasons.

Only 13 percent of farmers have employ improved maize, and the remaining 87 percent employ local maize. Farmers report a preference for local maize because they consider it to be less prone to drought, flood and pest attack after harvest. Higher yields is the most cited reason given by adopters of improved maize variety.

4. Theoretical Framework

Consider an individual farmer who owns a farm of a given size L. At the beginning of each agricultural season he must decide which variety of seed and quantity to purchase for his farming activity. At planting, he faces an uncertain weather. Weather can be "bad" with probability ρ or "good" with probability $1-\rho$. Following Feder (1980) and Just and Pope (1978), we assume a constant returns to scale production function with one variable input, x (fertilizer), and one fixed variable factor (land). The output per unit of land is given by $y = f(x)$, where f is a positive, strictly increasing, strictly concave, twice continuously differentiable production function. The output realized by the farmer at harvest if weather is good is $y = f(x)$, while the output realized if the weather is bad is $y = \xi f(x)$, where $0 < \xi < 1$, measures the sensitivity of the crop to the bad weather and thus the riskiness of the crop. The output price p_y is normalized to 1 and the input price p_x and income are expressed in relative terms.

A risk neutral farmer maximizes his expected production income as follows:

$$\underset{x}{Max}\, E(y) = \{E[L(\rho\xi f(x) + (1-\rho) f(x))] - p_x.x.L\} \tag{2}$$

From the first-order condition:

$$f^{'}(\rho(\xi - 1) + 1) - p_x = 0 \tag{3}$$

From the implicit function theorem it follows that:

$$\frac{\partial x}{\partial \rho} = -\frac{f^{'}(\xi - 1)}{f^{"}(\rho(\xi - 1) + 1)} < 0 \tag{4}$$

$$\frac{\partial x}{\partial \xi} = -\frac{f^{'}\rho}{f^{"}(\rho(\xi - 1) + 1)} > 0 \tag{5}$$

$$\frac{\partial x}{\partial p_x} = \frac{1}{f^{"}(\rho(\xi - 1) + 1)} < 0 \tag{6}$$

Equations (3) and (4) describe the fertilizer use per unit of land responses of the risk neutral farmer to the changes in the probability of a bad season outcome and the sensitivity of the crop to the bad season. This implies that a risk avrese farmer would reduce fertilizer input if either the likelihood of bad weather increases or the sensitivity of the crop to the bad weather increases. Because farm size does not appear in equation (2), fertilizer use is independent of farm size (Feder, 1980).

Equation (1) does not include the weighting of probabilities. If the individual farmer is uncertain about the probability of a bad weather and therefore has a subjective probability rather than an objective probability (Savage, 1954), the subjective probability may substitute for the objective probability in equation (1). Farmers in developing countries are generally observed to overweight low probabilities and underweight high probabilities relative to objective probabilities (Gonzalez & Wu, 1999; Kahneman & Tversky, 1979).. As such, a farmer who overweighs the probability of a bad year and underweighs the probability of a good year will use less fertilizer.

Partial adoption of a new technology requires either a trade-off between expected return and expected risk or some other constraints to adoption, such as limited access to inputs, lumpiness, fixed transactions costs with adoption of the new technology, or heterogeneous farming conditions. Uncertainty about future states of nature may be another reason for partial adoption and heterogeneity in adoption. That is because a farmer may want to test the new technology first before he or she fully adopts it.

4.1. Maize Variety Adoption

We focus on ex-ante maize and fertilizer choice and application intensity decisions and assume that a non-separable farm household model provides an appropriate framework for household input decisions, given input markets are imperfect (Ricker-Gilbert, Jayne, & Chirwa, 2011). In particular, for the purposes of estimation, we assume

$$\begin{aligned} M_i^M; IM_i^M &= \alpha_0^M + \alpha_1^M \sigma_i + \alpha_2^M \mu_i + \alpha_3^M A_i + \alpha_4^M E_i + \alpha_5^M PC_i + \alpha_6^M D_i^{2014} + \ldots \\ &\alpha_7^M ND_i + \alpha_8^M HC_i + \alpha_9^M ISS_i \left(\alpha_{10}^M LE_i + \alpha_{11}^M LR_i + \alpha_{12}^M S_i + \alpha_{13}^M M_i^{\#M}\right) + \alpha_{14}^M D_j; ipw_i \end{aligned} \quad (7)$$

where M_i^M is a dummy variable indicating which variety of maize is grown by the household and IM_i^M a measure of the intensity of adoption of that variety of maize. The intensity of adoption is measured as the quantity of maize seed variety planted. The relative risk aversion coefficients σ_i and the subjective probability weights μ_i were elicited using Holt and Laury's (2002) Multiple Price List data. A_i is the aspiration index. We believe that farmers who have a high aspiration index will be more willing to adopt high yield maize. The variable D_i^{2014} is a binary dummy variable that takes the value one if drought was experienced in the preceding growing season, ND_i is the number of droughts experienced over the previous five seasons. The variable ISS_i includes idiosyncratic shocks such as death or serious illness in the household. Such shocks are expected to affect the ability and willingness to adopt and the intensity of adoption. HC_i are other exogenous household characteristics such as farm size, gender and age of household head, household dependency ratio, etc.

Farm size may limit the decision and the intensity of adoption. As farmer may choose to experiment with a new technology on one part of the farm without significantly deviating from his normal agricultural practice in other parts. The variables in parentheses are endogenous in nature, and we estimate our models with and without them to assess the stability of the estimates and the potential importance of these endogenous variables: household endowment in livestock (LE_i), household loan received (LR_i), household saving (S_i) and the intensity of adoption of other maize varieties $(M_i^{\#M})$. We assume that high yield maize is a substitute for local maize and therefore expect negative correlations between the intensity of adoption of high yield and local maize, due to constrained access to land, labor and liquidity for input purchase. ipw_i is the inverse probability weight, included in the model to control for attrition in the sample. District fixed effects (D_d) were also used to control for cross district differences in market access, prices and the availability of high yield maize variety.

To estimate the coefficients, we used a double hurdle model. The average partial effects (APEs) were obtained for each of the two hurdles for the key variables of interest based on Burke (2009), and standard errors were derived using bootstrapping with 400 replications for key variables for one APE at the time.

4.2. Fertilizer Use

Most studies that look at the intensity of fertilizer do not distinguish among different types of fertilizer, although different types of fertilizer carry different levels of risk. One novelty of this study is that we consider three different varieties of fertilizer: organic, inorganic compound and inorganic straight fertilizer. We estimate intensity of fertilizer use for the two maize varieties (local maize and high yield maize). We express fertilizer use in natural logarithms. For observations with no fertilizer use, we added one unit of fertilizer so that we can be able to take their log transformation. To handle attrition and selection bias, inverse probability weights $\left(ipw_i^M\right)$ were generated for households having a given maize variety using probit models with household characteristics. The fertilizer intensity models were then weighted with these IPWs (inverse probability weights). Fertilizer intensity models were estimated for each maize variety as censored Tobit model.

$$
\begin{aligned}
F_{ij}^{M} = {} & \beta_0^M + \beta_1^M \sigma_i + \beta_2^M \mu_i + \beta_3^M A_i + \beta_4^M E_i + \beta_5^M PC_i + \beta_6^M D_i^{2014} + \beta_7^M ND_i + \beta_8^M HC_i + \beta_9^M ISS_i \\
& \left(\beta_{10}^M LE_i + \beta_{11}^M LR_i + \beta_{12}^M S_i + \beta_{13}^M M_i^{\#M} + \beta_{14}^M F_{i\#j}^{\#M}\right) + \beta_{15}^M D_v ; ipw_i^M \qquad (8)
\end{aligned}
$$

The dependent variables are in log-form and are left censored. $F_{i\#j}^{\#M}$ is the quantity of fertilizers applied in the other maize variety.

We estimate equations (7) and (8) to test the following hypotheses:

H1) Higher relative risk aversion is negatively associated with reduces the probability and intensity of adoption of high yield maize.

H2a) Subjective overweighting of low probabilities is positively associated with the intensity of adoption of high yield maize and fertilizer use on high yield maize.

H2b) Subjective overweighting of low probabilities is positively associated with the intensity of adoption of high yield maize and fertilizer use on high yield maize.

H3a) Previous experience with drought is negatively associated with the probability of adoption and intensity of adoption of high yield maize.

H3b) Previous experience with drought is negatively associated with the intensity of adoption of high yield maize.

H4) Higher aspiration is positively associated with the probability and intensity of adoption of high yield maize.

H5) Peer consultation is positively associated the probability and intensity of adoption of high yield maize.

5. Estimation Results

5.1.Maize Type Adoption

Table 3 and Table 4 show the estimates of the double hurdle models for adoption and intensity of adoption of the two types of maize respectively. The second and the third columns in Table 3 and Table 4 exclude endogenous variables, while the four and fifth columns include endogenous variables. Average partial effects (APE) of principal variables are presented in Table 5.

We first examine the factors associated with the adoption of different varieties of maize. The estimates for the first hurdle (probability of adoption) show that relative risk aversion is significantly negatively correlated with high yield maize adoption (five percent level), while relative risk aversion is significantly positively correlated with local maize adoption (five percent level). The corresponding average partial effects in Table 5 further suggest that local maize is considered to be the safer option. It indicates that a risk averse farmer with “CRRA=2” is 20 percent more likely to plant local maize than a farmer with “CRRA=1”, while he is 50.5 percent less likely to adopt high yield maize.

Peer consultation, which is measured by the number of people (other farmers in the community) the respondent consults before taking any important agricultural decision, is significantly positively correlated with high yield maize adoption (five percent and one percent level, respectively, for the models with and without the endogenous variables included), and significantly negatively correlated with the adoption of local maize (five percent level). The corresponding average partial effects in Table 5 show similar results but significant at the five percent level for both high yield and local maize. Table 5 indicates that a farmer with two peer consultations is 12 percent more likely to adopt high yield maize variety that a farmer with one peer consultation, while he is one percent more likely to dis-adopt local maize. This suggests that farmers either lack adequate information about the new technology or prefer not to be the first in the community to adopt it.

The preceding season drought dummy is significantly negatively correlated with adoption of high yield maize (one percent level) in both model specifications in Table 3. The average partial effect in Table 5 is also significantly negatively correlated with adoption of high yield maize (one percent level). As seen in Table 5, farmers exposed to drought in 2014 were 57.1 percent less likely to plant high yield maize in 2015.

Household food security status is significantly positively correlated local maize adoption (one percent level) in both model specifications in Table 3. The average partial effect in Table 5 is also significantly positively correlated with local maize adoption (one percent level). Table 5 indicates that a severely food insecure farmer is 20 percent more likely to continue using local maize than one who is moderately food insecure. This suggests that food insecure farmers may not have sufficient money to buy new seeds or may consider local maize production to reduce variation in their food intake.

Among the other exogenous variables, only sex of the household head is significant in both specifications in Table 3 and in Table 5 (10 percent level). Male headed households are significantly more likely to adopt high yield maize compared to female headed households (10 percent) level in both models in Tables 3 and 5. Table 5 shows that a male-headed households are 32.3 percent more likely to adopt high yield maize than a female headed household.

Among the endogenous variables (savings, loan received and livestock endowment) included in the second set of the models, household saving is positively correlated with the adoption of high yield maize (significant at the five percent level in Table 3), Household loan received is also significantly positively correlated at the one percent level with high yield maize and at the five percent level with local maize and livestock endowment, as measured in “Tropical Livestock Units”, are positively correlated with both high yield and local maize (at the one percent level in both in Tables 3 and 5). For average partial effects in Table 5, household saving is positively correlated with the adoption of high yield maize at the five percent level (farmers with 100 Ghana cedi saving are four percent more likely to adopt high yield maize than farmers without saving), household loan received is also significantly positively correlated with the adoption of high yield maize at the one percent level (farmers who received 100 Ghana cedi credit are 33.3 percent more likely to adopt high yield maize than farmers who did not receive credit). This is probably due to the fact that savings, credit and livestock provide farmers with the money and security needed to adopt high yield but risky technologies and this may indicate that liquidity can constrain adoption of high yield maize as also found by Feder (1980). The high magnitude of loans received may be explained by the fact that most of the loan received are cashless; in the form of seed or/and fertilizer.

We then follow with an assessment of factors that explain the intensity of adoption of different maize varieties. The second hurdle estimations in Table 4 show that factors that determine the intensity of adoption differ from those that affect the first stage adoption decision.

Relative risk aversion is negatively related to the intensity of adoption of high yield maize (10 percent level) but positively correlated with the intensity of adoption of local maize (five percent level). The average partial effects in Table 5 are significant (five percent level) with negative sign for the high yield maize and positive sign for the local maize. Thus, a farmer with CRRA=2 plants 54 percent less high yield maize and 17.8 percent more local maize than a farmer with CRRA=1.

The subjective probability weight parameter is significantly negatively correlated with the intensity of adoption of high yield maize at the five percent level in both specifications in Table 4. The average partial effect in Table 5 is also negatively related to the intensity of adoption of high yield maize at the one percent level, although the average partial effect is significant it has a very small effect (0.3 percent) on the intensity of adoption of high yield maize.

The aspiration index, although statistically insignificant in the adoption decision models, is significantly positively correlated with the intensity of adoption of high yield maize at the five percent level in both specifications in Table 4. The average partial effect is also significant at the five percent level with a positive sign in Table 5. The estimation in Table 5 shows that highly aspired farmer who plants high yield maize, will plant 2.5 percent more high yield maize than a non-aspired farmer who plants high yield maize.

Table 3: Parameter Estimates for Double Hurdle Models by Maize Variety, with and without Endogenous Variables (Hurdle 1).

Hurdle 1: Variety of Maize Planted	Without Endogenous Variables		With Endogenous Variables	
	High Yield Maize	Local Maize	High Yield Maize	Local Maize
Relative Risk Aversion.	-2.081**	0.586**	-1.001*	1.503**
	(2.454)	(2.040)	(3.986)	(3.903)
Subjective Probability Weight	0.383	-0.239	0.316	-0.639
	(1.253)	(0.632)	(2.995)	(0.829)
Aspiration Index	0.137	0.798	0.215	0.768
	(0.131)	(0.414)	(0.156)	(0.468)
Drought Perception	-0.533	0.112	-1.525	-0.443
	(0.522)	(0.220)	(1.148)	(0.264)
Peers Consultations	0.092***	-0.071**	0.021**	-0.061**
	(0.043)	(0.041)	(0.084)	(0.096)
Drought in 2014, Dummy	-0.487***	0.444	-0.086***	0.621
	(0.164)	(0.276)	(0.570)	(0.415)
Number of Drought, Previous 5 Seasons	-0.022	-0.005	-0.184	-0.027
	(0.055)	(0.141)	(0.160)	(0.177)
Medical Emergencies in Household	0.302***	-0.276***	-0.118	-0.113
	(0.093)	(0.046)	(0.196)	(0.179)
Death of Household Member	0.102	-0.248**	-0.118	-0.413**
	(0.374)	(0.102)	(0.375)	(0.179)
Log Farm Size (Acres)	0.272	0.280	0.250	0.087
	(0.216)	(0.175)	(0.435)	(0.115)
Distance to Market (Minutes)	-0.003***	0.003***	-0.002***	0.001***
	(0.001)	(0.002)	(0.002)	(0.001)
Food Security Status	-0.016	0.012***	-0.004	0.050***
	(0.055)	(0.005)	(0.110)	(0.036)
Sex of Household Head (1. Male, 0. Female)	0.233*	-0.089	0.693*	-0.021
	(0.298)	(0.219)	(0.404)	(0.422)
Age of Household Head	-0.003	-0.004	-0.003	0.002
	(0.006)	(0.005)	(0.024)	(0.005)
Level of Education	0.096	-0.148	0.102	-0.060
	(0.072)	(0.095)	(0.064)	(0.045)
Household Dependency Ratio	-0.139	0.044	-0.484	0.046
	(0.153)	(0.064)	(0.353)	(0.010)
Household Savings (100 GHS)			0.014**	0.051
			(0.062)	(0.026)
Household Loan Received (100 GHS)			0.142***	0.154*
			(0.042)	(0.079)
Livestock Endowment (TLU)			0.035***	0.028***
			(0.004)	(0.002)

Table 4: Parameter Estimates for Double Hurdle Models by Maize Variety, with and without Endogenous Variables (Hurdle 2).

Hurdle 2: Quantity of Maize Variety Planted	Without Endogenous Variables		With Endogenous Variables	
	High Yield Maize	Local Maize	High yield Maize	Local Maize
Relative Risk Aversion	-0.508*	0.630**	-0.610*	0.538**
	(0.629)	(0.413)	(0.045)	(0.977)
Subjective Probability Weight	-0.762**	0.753	-0.938**	0.752
	(1.935)	(3.562)	(1.234)	(1.803)
Aspiration Index	0.044**	0.101	0.396**	0.458
	(2.127)	(0.200)	(1.611)	(0.325)
Drought Perception	-1.789	0.111	-1.740	-0.464
	(1.620)	(1.607)	(2.009)	(0.873)
Peers Consultation	0.128**	0.118	0.093**	0.116
	(0.128)	(0.109)	(0.140)	(0.089)
Drought 2014, Dummy	-2.926	-0.547	-1.236	-0.594
	(1.731)	(0.377)	(1.386)	(0.413)
Number of Drought, Previous 5 Seasons	-0.770	-0.371	-0.553	-0.396
	(0.753)	(0.462)	(0.717)	(0.395)
Medical Emergencies in Household	1.184	-0.438	0.822	-0.184
	(1.722)	(0.321)	(1.433)	(0.349)
Death of Household Member	-1.182	-1.280**	-0.942	-1.279***
	(1.800)	(0.510)	(1.321)	(0.357)
Festival in the Household	-0.838	0.991***	-0.274	0.813*
	(1.031)	(0.377)	(1.015)	(0.456)
Log Farm Size (Acres)	0.184***	0.407***	0.150***	0.112***
	(1.835)	(1.229)	(0.411)	(0.291)
Distance to Market (Minutes)	0.002	0.006	0.003	0.000
	(0.006)	(0.007)	(0.001)	(0.002)
Food Security Status	0.296	0.046	0.049	-0.095
	(0.742)	(0.303)	(0.249)	(0.058)
Sex of Household Head (1. Male, 0.Female)	-0.089	1.952	-0.323	1.845
	(1.371)	(0.447)	(0.999)	(0.301)
Age of household Head	-0.001	-0.027**	-0.025	-0.032
	(0.023)	(0.012)	(0.039)	(0.023)
Level of Education	1.139	0.626	1.218	1.024
	(1.415)	(0.514)	(1.206)	(0.321)
Household Dependency Ratio	-0.595	0.250	-0.514	0.199***
	(0.937)	(0.180)	(0.756)	(0.030)
Household Savings (100 GHS)			0.060**	0.107**
			(0.049)	(0.048)
Household Loan Received (100 GHS)			0.179	-0.071
			(0.171)	(0.089)
Livestock Endowment (TLU)			0.288***	0.202***
			(0.043)	(0.036)

Table 4: Continued

Hurdle 2: Quantity of Maize Variety Planted	Without Endogenous Variables		With Endogenous Variables	
	High Yield Maize	Local Maize	High Yield Maize	Local Maize
Log of Local Maize Seed Qty			-2.679*	
			(1.619)	
Log of High Yield Maize Seed Qty				-1.604***
				(0.518)
District FE	Yes	Yes	Yes	Yes
Constant	11.841	-8.206	11.137	-10.367
	(15.433)	(10.927)	(18.238)	(9.926)
Sigma Constant	10.791*	5.003***	9.915*	4.155***
	(5.755)	(0.528)	(5.793)	(0.512
Log likelihood	-12606	-1197	-12325	-1124
Observations	331	331	331	331

Note: *, **, *** indicate that coefficients are significant at 10, 5, and 1% levels, respectively. Standard errors in parentheses. Models weighted with inverse probability weights to correct for attrition bias, based on household characteristics. Models estimated using Craggit command in Stata 14. The table gives average marginal effects.

Peer consultation is significantly positively correlated with the intensity of adoption of high yield maize in both specifications in Tables 4 and 5. The average partial effects in Table 5 imply that 10 percent increase in peer consultations is associated with 0.14 percent increase in the quantity of high yield maize planted.

Farm size is significantly positively correlated at the one percent level across the two varieties of maize and in both specification in Tables 4 and 5. A one percent increase in farm size is associated with a 0.16 percent increase in the area of high yield maize and a 0.14 percent increase in the area of local maize. This shows that small farm size is a major constraint on smallholder intensity of adoption.

Among the endogenous variables, only saving is significant in both Tables 4 and 5. Household saving is positively correlated with the intensity of adoption of both maize variety (five percent level). Table 5 indicates that farmers with 100 Ghana cedi saving are more likely to increase their high yield maize use by 0.4 percent and their local maize use by 0.1 percent.

Table 5: Average Partial Effects (APEs) with Bootstrapped Standard Errors

Maize Variety	High Yield Maize		Local Maize	
Hurdle 1: Growing Maize Variety	APE	BootstrSE	APE	Bootstr SE
Relative Risk Aversion	-0.505**	0.198	0.303**	0.200
Subjective Probability Weight	0.131	0.019	0.523	0.045
Aspiration Index	0.167	0.145	0.256	0.176
Peers Consultation	0.12**	0.011	-0.01**	0.122
Drought 2014, Dummy	-0.571***	0.177	0.012	0.123
Number of Droughts, Previous 5 Seasons	-0.145	0.043	-0.075	0.034
Medical Emergencies in Household	-0.301***	0.067	-0.203***	0.033
Death of Household Member	-0.103	0.002	-0.422**	0.100
Log Farm Size (Acres)	-0.025	0.023	0.022	0.111
Distance to Nearest Market (Minutes)	-0.210***	0.356	0.013	0.121
Food Security Status	-0.233	0.432	0.200***	0.134
Age of household Head	-0.014	0.020	0.004	0.045
Sex of Household Head (1. Male, 0.Female)	0.013*	0.003	-0.024	0.223
Household Savings (100 GHS)	0.040**	0.054	0.194	0.056
Household Loan Received (100 GHS)	0.333***	0.140	0.001	0.459
Livestock Endowment (TLU)	0.055***	0.123	0.007***	0.662
Hurdle 2: Log of Quantity of Maize Seed Planted				
Relative Risk Aversion	-0.540**	0.340	0.178**	0.128
Subjective Probability Weight	-0.003***	0.168	0.123	0.328
Aspiration Index	0.025**	0.831	0.729	0.588
Expectation Index	0.179	0.458	-0.504	0.406
Peers Consultation	0 .014**	0.036	0.015	0.019
Drought 2014, Dummy	-0.453	0.014	0.210	0.697
Number of Droughts, Previous 5 Seasons	-0.369	0.837	-0.218	0.281
Medical Emergencies in Household	0.678	3.659	-0.300	0.659
Death of Household Member	-0.592	0.466	-0.504	0.553
Log Farm Size in Acres	0.164***	0.031	0.141***	0.056
Distance to Nearest Market (Minutes)	0.032	0.056	0.002	0.004
Food Security Status	-0.902	1.642	-0.206	0.186
Age of household Head	-0.182	0.224	-0.037*	0.020
Sex of Household Head (1. Male, 0.Female)	0.979	7.807	2.263***	0.857
Household Savings (100 GHS)	0.004**	0.004	0.001**	0.001
Household Loan Received (100 GHS)	0.001	0.007	-0.001	0.001
Livestock Endowment (TLU GHS)	0.233	0.281	0.109	0.054

Note: Average partial effects for the models in Table 3 including endogenous variables. Bootstrapped standard errors based on 400 replications programmed based on Burke (2009). *, **, *** indicate that coefficients are significant at 10, 5 and 1% levels, respectively.

We summarize the first findings in terms of our hypotheses: Our findings support hypothesis H1), which states that "*Relative risk aversion is positively associated with a lower probability and a lower intensity of adoption of high yield maize*". Our findings support hypothesis H2a too, which states that "*Subjective overweighting of low probabilities is positively associated with low intensity of adoption of high yield maize*", although the average marginal effect of subjective probability weighting parameter is very small (0.3 percent). Our findings also support hypothesis H3a, which states that "*Drought experience in previous seasons is positively associated with lower adoption of high yield maize*". The correlation between intensity of adoption and the drought experience, however, was not significant, so we do not accept hypothesis H3b. Our findings do not support Hypothesis H4, which states that "*Higher aspiration is positively associated with higher probability and higher intensity of adoption of high yield maize type*". We find that higher aspiration is associated with higher intensity of adoption of high yield maize, but not with the probability of adoption. Our findings support hypothesis H5, which states that "*Peer consultation is positively associated with high probability of adoption and high intensity of adoption of high yield maize*".

5.2. Fertilizer Type Adoption

Fertilizer use by maize variety is analyzed using censored Tobit models that are conditional on the variety of maize being planted by households. To correct for attrition and sample selection bias related to planting specific varieties of maize, inverse probability weights from probit models for planting each variety were used, with household characteristics as right-hand side variables. We distinguished among three types of fertilizer (organic, inorganic compound and inorganic straight). Tables 6 and 7 present estimates of average marginal effects for models without and with endogenous variables, respectively. Both tables indicate that estimates vary across fertilizer type. The heterogeneity in fertilizer type can be explained by the differences in price and risk (productivity and environmental).

Relative risk aversion is significantly negatively correlated with intensity use of inorganic compound fertilizers on high yield maize at the one percent level. Holden (2015) found similar results. But because we disaggregated fertilizer into different types, we were able to find that relative risk aversion is significantly positively correlated to the intensity of organic fertilizer use in both maize varieties and in both specifications (one percent level). This is particularly true in our study because almost 90 percent of farmers in our sample produce their own organic fertilizer. This result could not be found in the Holden (2015) because fertilizer variable was not disaggregated into different varieties.

The subjective probability weight is significantly positively correlated with both inorganic compound and inorganic straight fertilizer use, for both maize varieties and in both specifications at 1 to 10 percent. This indicates that farmers who overweight low probabilities use less inorganic compound and inorganic straight fertilizer on both varieties of maize.

Peer consultation is significantly positively associated with both inorganic compound and inorganic straight fertilizer use on high yield maize. Peer consultation is also significantly negatively correlated with inorganic compound fertilizer use on local maize.

Previous drought experience is significantly negatively correlated with all types of fertilizer use on all varieties of maize in the endogenous model setup (Table 7) but in the without endogenous model setup (Table 6), it is only on high yield maize variety. So farmers who experienced drought in the previous season use less fertilizer, perhaps because they consider it riskier as they still have the memory of the shock.

Among the endogenous variables included in Table 7, saving and loan received are significantly positively correlated with inorganic compound and straight fertilizer use on high yield maize. This suggests that credit and liquidity constraints limit fertilizer use intensity.

We now summarize our finding with regard to the remaining hypotheses on fertilizer use intensity. First, hypothesis H2b, we did not find a consistent result in regard across the three types of fertilizers. Only inorganic compound and inorganic straight fertilizer types satisfy this hypothesis. The organic fertilizer gave a reverse result. The hypothesis, therefore, cannot be accepted. This contradicts the results reported by Holden (2015).

Table 6: Censored Tobit for Intensity of Fertilizer Use by Maize Variety without Endogenous Variables

Parameters	Organic Fertilizer		Inorganic Compound Fertilizer		Inorganic Straight Fertilizer	
	High Yield Maize	Local Maize	High yield Maize	Local Maize	High Yield Maize	Local Maize
Relative Risk Aversion	0.083***	0.552***	-0.277	-3.144	-0.789***	-0.339
	(0.467)	(0.185)	(0.175)	(0.227)	(0.124)	(0.404)
Subjective Probability Weight	-2.777	-1.752	3.124**	1.093**	5.917**	0.497***
	(0.423)	(0.469)	(0.9.36)	(0.400)	(0.793)	(0.540)
Aspiration Index	-1.936	1.257	-0.860	1.009***	-0.277	0.966***
	(2.447)	(0.986)	(0.824)	(0.258)	(1.072)	(0.124)
Peers Consultation	1.256	-0.234	0.690***	-0.084**	0.406**	0.020
	(1.148)	(0.173)	(0.379)	(0.042)	(0.321)	(0.044)
Drought 2014, Dummy	-0.126***	-1.416	-0.387***	0.524	-5.115***	0.317
	(2.716)	(1.424)	(0.947)	(0.346)	(0.540)	(0.461)
Number of Drought, Previous 5 Seasons	-3.279	-0.605	-0.279	-0.148	0.033	-0.239
	(2.080)	(0.670)	(0.415)	(0.256)	(0.323)	(0.225)
Medical Emergencies	0.750	-0.623	0.212***	-0.388***	2.635***	-0.570***
	(2.746)	(0.992)	(0.538)	(0.114)	(0.291)	(0.064)
Death of Household Member	-1.659	-0.131	0.857	-0.535*	-2.163	-0.426*
	(3.585)	(0.828)	(2.897)	(0.303)	(2.272)	(0.223)
Log Farm Size (Acres)	-0.636	3.139***	-1.723	0.805**	-1.414	0.875***
	(3.389)	(0.514)	(1.492)	(0.323)	(1.388)	(0.196)
Distance to Market	-0.014	-0.018**	-0.021***	0.002	-0.025***	0.003**
	(0.021)	(0.009)	(0.006)	(0.003)	(0.008)	(0.002)
Food Security Status	0.293	0.361	-0.048	0.094***	-0.177	0.114
	(1.759)	(0.455)	(0.481)	(0.031)	(0.380)	(0.077)
Sex of Household Head (1. Male, 0.Female)	12.259*	2.250*	1.897	0.047	4.507***	0.274
	(6.596)	(1.189)	(2.076)	(0.274)	(1.068)	(0.226)
Age of household Head	-0.481***	0.020	-0.020	0.000	-0.032	-0.005
	(0.109)	(0.080)	(0.038)	(0.010)	(0.035)	(0.009)
Level of Education	2.930***	-1.095	0.775	-0.208	0.868*	-0.094
	(1.088)	(1.047)	(0.526)	(0.251)	(0.491)	(0.312)
Household Dependency Ratio	-0.696	-0.825*	-1.124	-0.046	-0.454	0.106
	(2.951)	(0.473)	(1.263)	(0.047)	(0.987)	(0.084)
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-10.482	-1.167	-20.349**	4.704**	-28.124***	0.672
	(49.354)	(11.851)	(8.781)	(1.986)	(10.237)	(2.313)
Sigma Constant	16.008***	7.804***	8.019***	2.155***	7.343***	2.206***
	(1.372)	(0.309)	(0.653)	(0.183)	(1.066)	(0.080)
Log likelihood	-1170	-806.7	-1747	-796.2	-1508	-783.5
Observations	331	331	331	331	331	331

Table 7: Censored Tobit for Intensity of Fertilizer use by Maize Variety with Endogenous Variables

Parameters	Organic Fertilizer		Inorganic Compound Fertilizer		Inorganic Straight Fertilizer	
	High Yield Maize	Local Maize	High Yield Maize	Local Maize	High Yield Maize	Local Maize
Relative Risk Aversion	0.252***	0.134***	-0.798	-0.447	-0.230***	-0.575
	(0.678)	(0.192)	(0.657)	(1.444)	(7.617)	(2.841)
Subjective Probability Weight	-0.316	-0.624	0.846*	1.422***	0.609***	1.696***
	(0192)	(0.513)	(0430)	(0.341)	(1.980)	(0.651)
Aspiration Index	-1.124	-0.573	0.317	0.360***	-0.354	0.176
	(1.953)	(0.617)	(0.518)	(0.058)	(0.573)	(0.125)
Peers Consultation	-0.781	-0.145	0.049***	-0.082**	0.003***	0.103
	(0.832)	(0.108)	(0.076)	(0.023)	(0.160)	(0.019)
Drought 2014, dummy	-5.647**	-1.931**	-1.914*	-0.279***	-0.970***	-0.087***
	(2.862)	(0.970)	(1.061)	(0.104)	(0.210)	(0.278)
Number of Drought Previous 5 Seasons	-2.992***	-0.300	-0.110	0.027	0.317*	-0.148***
	(0.901)	(0.301)	(0.147)	(0.076)	(0.175)	(0.033)
Medical Emergencies in Household	6.607***	0.073	-1.000*	0.134**	0.595**	-0.286*
	(1.356)	(1.103)	(0.603)	(0.055)	(0.248)	(0.156)
Death of Household Member	-3.117*	0.691	1.587**	-0.229	-1.821***	0.007
	(1.879)	(1.273)	(0.717)	(0.197)	(0.621)	(0.074)
Festival in the Household	2.567	0.502	-1.663**	0.128	0.560**	-0.051
	(2.318)	(0.788)	(0.826)	(0.125)	(0.258)	(0.114)
Log Farm Size (Acres)	1.077	1.370	0.135	0.020	0.122	0.149
	(2.976)	(0.934)	(0.544)	(0.117)	(0.424)	(0.141)
Distance to Market (Minutes)	0.098***	-0.014**	0.003**	-0.000	-0.008	0.001
	(0.018)	(0.007)	(0.001)	(0.001)	(0.010)	(0.001)
Food Security Status	1.094	0.173	0.293*	0.008	0.101	0.038
	(0.700)	(0.413)	(0.156)	(0.056)	(0.107)	(0.091)
Sex of Household Head (1. Male, 0.Female)	5.177	2.036**	-2.312***	-0.187*	1.944**	0.286***
	(3.192)	(0.993)	(0.815)	(0.113)	(0.863)	(0.044)
Age of Household Head	-0.586***	0.026	0.063	0.003	-0.034	-0.007
	(0.180)	(0.087)	(0.040)	(0.008)	(0.021)	(0.006)
Level of Education	3.526***	-1.023	0.045	-0.039	-0.160	0.093
	(0.880)	(0.645)	(0.282)	(0.096)	(0.535)	(0.144)
Household Dependency Ratio	-0.104	-0.550	-0.611	-0.096	0.072	0.127
	(1.112)	(0.540)	(0.516)	(0.083)	(0.285)	(0.081)

Table 7: Continued

Parameters	Organic Fertilizer		Inorganic Compound Fertilizer		Inorganic Straight Fertilizer	
	High Yield Maize	Local Maize	High Yield Maize		High Yield Maize	Local Maize
Household Savings (100 GHS)	0.354	0.209*	0.082***	-0.005	0.050***	0.003
	(0.605)	(0.118)	(0.094)	(0.004)	(0.036)	(0.012)
Household Loan Received (100 GHS)	-0.463*	-0.238	0.345***	0.027	0.017***	-0.074
	(0.267)	(0.205)	(0.263)	(0.026)	(0.109)	(0.019)
Livestock Endowment (TLU)	0.029	0.016	0.016	0.014***	0.005	0.012
	(0.032)	(0.021)	(0.017)	(0.005)	(0.007)	(0.007)
Log Organic Fertilizer/Local Maize	0.873***			0.059***		0.004
	(0.128)			(0.010)		(0.020)
Log Compound Fert/High Yield Maize	6.179***			-0.359*	1.672***	
	(0.500)			(0.185)	(0.121)	
Log Straight Fert/ High Yield Maize	-0.979		1.561***			0.205
	(1.052)		(0.051)			(0.302)
Log of Local Maize Seed Qty	-8.932***		-1.763		-1.793***	
	(1.424)		(1.177)		(0.425)	
Log Organic Fert/ High Yield Maize		0.576***	0.217**		0.036	
		(0.204)	(0.087)		(0.064)	
Log Compound Fert/Local Maize		2.030***	-0.076			0.961***
		(0.283)	(0.114)			(0.082)
Log Straight Fert/Local Maize		0.079		0.721***	0.522***	
		(0.401)		(0.138)	(0.096)	
Log of High Yield Maize Seed Qty		-4.233**		-0.166		-1.233
		(2.021)		(0.345)		(1.013)
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	35.404	-11.801	-2.551	3.620***	-16.076**	-3.919***
	(24.165)	(13.653)	(5.617)	(1.365)	(7.246)	(1.047)
Sigma Constant	3.214***	6.749***	1.524***	1.074***	0.867***	1.154***
	(0.356)	(0.205)	(0.375)	(0.060)	(0.230)	(0.143)
Observations	331	331	331	331	331	331
Log likelihood	-541.3	-757.8	-723.2	-528.8	-412.1	-532.5
Observations	331	331	331	331	331	331

Note: Dependent variable: log (kg Fertilizer+1). *, **, *** indicate that coefficients are significant at 10, 5 and 1% levels, respectively. Standard errors in parentheses. Models weighted with inverse probability weights to correct for attrition bias and sample selection into maize variety, based on household characteristics. The models are conditional on each maize variety being grown by the household. The coefficients are average marginal effects.

6. Conclusion

We have assessed maize and fertilizer adoption decisions of smallholder farmers in Ghana. Field experiments were used to elicit risk preferences (relative risk aversion and subjective probability weight) parameters. These were combined with detailed household information including saving, loan received, age and gender of the household head, household head aspiration index, types and quantities of maize varieties planted, types and quantities of fertilizer used, and household head peer consultations on important agricultural decisions.

First, we found that more risk averse farmers are more likely to plant local maize and less likely to plant high yield maize. We also found relative risk aversion to be positively associated with high intensity of organic fertilizer application on both high yield and local maize. Second, we found that farmers who consult with other farmers before taking important agricultural decisions are more likely to adopt high yield maize. We also found that greater peer consultation is positively associated with more inorganic compound and straight fertilizer use on high yield maize and less on local maize. Third, previous drought experience was negatively associated with the adoption of high yield maize. Farmers who experienced drought also used less fertilizer. Fourth, we found high aspirations to be positively associated with greater adoption of high yield maize. Finally, farmers who overweight low probabilities used less inorganic compound and inorganic straight fertilizer on both varieties of maize.

Although preferences and beliefs are not the primary focus of any policy intervention, they are invaluable to help explain observed behavior of individuals, households and firms. This study shown how taking into consideration risk preferences, subjective belief and risk experience can bring more inside on the behavioral determinant of agricultural technology adoption decision in developing countries. Our findings make important contribution to the smallholder farmers' behavioral implication on technology adoption in developing countries.

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