Drivers of Weedicide Adoption among Peseant Maize Farmers in the Northern Region of Ghana

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Abstract: **Globally, weeds wreak significant damages on plants and this situation calls for instantaneous measures to overcome the harm done by the weeds. Weeds can be removed by hand/hoe weeding but these are time consuming, laborious and do not even promise thorough removal of weeds. Weeds control through such traditional method has even become much problematic in Ghana as large portions of the rural youth, especially from the Northern Region, are migrating to the urban centers. Weedicide, on the other hand, offers a considerable promise of thoroughly removing weeds using few labours and time. However, there is evidence of low weedicide adoption among maize farmers in the Northern Region of Ghana. It is against this background that this study investigates the drivers of weedicide adoption among maize farm households in the Northern Region of Ghana. To achieve this objective, a correlated random-effects probit model was applied to a 3-year panel data from Innovation for Poverty Action-Farmer Survey of Ghana. A sample of 1728 peasant farm households was used for the study. The analysis of data revealed that dependency ratio, price of weedicide and communal labour were negatively related to weedicide adoption. It was also found that farm income, NPK fertilizer, other inorganic fertilizer, and the price of labour were positively related to weedicide adoption. It is recommended that: government should reduce dependency ratio through job creation and birth rate, subsidize weedicide, and promote the use of complementary farm inputs.**

Keywords: **Weedicide, adoption, maize, correlated random effect probit, dependency ratio, Ghana.**

I. INTRODUCTION

Maize production per hectare is very low (1.3 tonnes per hectare) in developing countries (IITA, 2007). In Ghana, maize yield are often less than 1 tonne per hectare, while the maize cultivars have a potential of more than 4 tonnes per hectare (Aflakpui *et al*., 2005). According to Tollenaar *et al.* (1997), yield reduction in maize results mostly from high competition between the crop and weed for water, light, nutrients and carbon dioxide. Poor crop management, notably inadequate weed control resulting in maize yield losses ranging from 50 to 90 percent (Chikoye *et al.*, 2005).

Farmers undertake weed control, but it is one of the most labour intensive activities for small-scale farmers, especially those in areas of high temperature (Hillocks, 1998). Cultural, biological and chemical measures are the main mechanisms for controlling weeds. Although cultural methods are still useful tools, they are laborious, time consuming and expensive, especially when labour problem is becoming severe day by day. This is the biggest challenge to most farmers but more especially farmers in the Northern region of Ghana since most of the youth migrate to the urban centers for greener pastures.

The use of weedicide is by far a much more effective weed control practice than hand hoe weeding when done timely twice or thrice in maize production (Mathews, 1984; Chikoye *et al*., 2002). However, the use of the hand hoe is time-consuming, back-breaking and expensive, especially where labour is scarce. Zimdahl (1983) discovered that the hand hoe weeding alone accounts for 40-54 percent of the total labour input in farming in Ghana, Nigeria, Burkina Faso, Sierra Leone, Malawi, Zambia, Ethiopia and Tanzania, requiring 300-400 man- hours per hectare. In most cases, due to limitations on family labour, farmers are unable to do their weeding on time. Considering all the limitations of cultural methods of weed control, chemical weed control is an important alternative.

Several research works have addressed the importance of weedicide use in maize. For example, Miller and Libby (1999) have reported that corn yield responded positively when weeds were controlled by weedicide. Becker and Staniforth (1981) obtained higher yield in maize with weedicide as compared to cultural weed control. Jehangeri *et al.* (1984) reported that application of selective weedicide provided 65 to 90 percent weed control and gave 100-150 percent more maize yield than the weedy check. In maize, mechanical weed control was 25 percent to 44 percent less effective than that obtained with weedicide and gave a yield reduction from 6 percent to 18 percent (Balsari, 1993). Naveed *et al.* (2008) revealed in their study that weedicide application is an efficient way to check weed infestation and increases maize production. In Ghana, Ragasa, Dankyi, Acheampong, Wiredu, Chapoto, Asamoah, and Tripp (2013) argued that a plot treated with weedicide records an appreciable yield than those without weedicide, with the greatest gap in the Northern Savannah Zone.

Using a simple comparison of the two weed control system, Ragasa *et al.* (2013) discovered that it was less costly (GHC 359 per hectare for enough weedicide for a hectare and additional 41mandays) to use weedicide than without using weedicide (GHC 511 per hectare for manual weeding for 73 man-days on the average). It is quite obvious that using weedicide is less expensive than hiring labour or using household labour for weeding. Owing to this, there has been a wide (73 percent of maize farmers nationwide) usage of weedicide in Ghana (Ragasa *et al.*, 2013). However, the adoption rate varied among the cropping zones in Ghana. Ragasa *et al.* (2013) revealed that weedicide adoption is high in the Forest, Transitional, and coastal zones ranging between 74 to 87 percent while Northern Savannah zone record 39 percent weedicide adoption.

Despite the importance of weedicide and the limited labour supply in the Northern region, the adoption of weedicide by maize farmers in this area is low. The critical question that comes to mind is: why is adoption rate of weedicide in the Northern region of Ghana low?

II. LITERATURE REVIEW

2.1Theoretical frame work

This study is premised on the non-separability of household production and consumption decisions (utility maximization theory) because markets in developing economies like Ghana are highly imperfect and/or missing. The theory postulates that farm household decisions would be more influenced by household size and structure, in the absence of labour market and unlimited supply of land (Chayanov, 1966).

This theory is justifiable not only because it have had the most comprehensive implications linking to development policy and practice, but also because it cover most segments of the peasant technology adoption debate. This theory assumes that farm households face a set of constraints as they maximize their objective functions. In addition, the theory is grounded on a set of assumptions about the workings of the wider economy and also clarifies farm household behaviour. The assumption of missing labour market and unlimited supply of land are the main flaws of this model in its novel form in the seminal work of Chayanov in the 1920s.

2.2Empirical literature

The literature on agricultural technology adoption is vast and somewhat tricky to summarize efficiently. So far, many scholars have concluded that adoption of agricultural technology is highly correlated to demand and supply factors. However, these demand and supply factors are difficult to separate when evaluating farmers' decisions to adopt agricultural technology. According to Mwangi (1995), the main determinants of agricultural technology adoption such as farm size, access to credit, membership in cooperatives, contact with extension, access to outside information, availability of inputs, and distance to markets can be related at least as much to supply facet constraints as to farmer demand factors.

Usually, economic analysis of agricultural technology adoption has focused on extreme weather, liquidity constraints, awareness of technologies (Diagne & Demont, 2007), risk and uncertainty (Koundouri, Nauges & Tzouvelekas, 2006; Simtowe *et al.*, 2006), imperfect information, institutional constraints, human capital, input availability (Feder, Just & Zilberman, 1985; Foster & Rosenzweig, 1996; Kohli & Singh, 1997), and availability of supportive infrastructure as potential explanations for adoption decisions (Feder, Just & Zilberman, 1985; Griliches, 1957; Kohli & Singh, 1997). A more contemporary constituent of literature focuses on social networks and learning (Foster & Rosenzweig, 1995; Bandiera & Rasul, 2002; and Conley & Udry, 2002).

Kohli and Singh (1997) also found that inputs played a huge role in the rapid adoption of HYVs in the Punjab. They indicated that the effort made by the Punjab government to make the technological innovations and their complementary inputs more easily and cheaply available allowed the technology to diffuse faster than in the rest of India. It is quite clear from this paper that the adoption of an innovation is seriously influenced by the availability and affordability of a related input (complementary input). The method had been theoretically sound because technology adoption decisions are inter-dependent, meaning that the decision to adopt one technology ought to enhance or deter adoption of other correlated technologies. However, the use of cross-sectional data ignores the dynamic elements of household adoption behaviour that could make the work much less appropriate for policy.

Of late, a significant body of literature on agricultural technology adoption has focused on the effect of social networks and learning. The basic inspiration behind this literature is the idea that a farmer, initially, in a village observes the behaviour of neighboring farmers (they may be in association or not), including their experimentation with new technology. Once a year's harvest is realized, the farmer then updates his or her priors concerning the technology which may increase his or her probability of adopting the new technology in the subsequent year. The elementary argument here is that adoption of technologies is influenced by Bayesian learning. For instance, Besley and Case (1993) used a model of learning where the profitability of adoption is indeterminate and exogenous. They found that once farmers realize the true profitability of adopting the new technology, they are more likely to adopt. Bandiera and Rasul (2002) also studied social networks and technology adoption in Northern Mozambique and found that the probability of adoption is higher amongst farmers who reported chit chat agriculture with others. Alternatively, using a target-input model of new technology which assumes that the best use of an input is unknown and stochastic, Foster and Rosenzweig (1995), and Conley and Udry (2002) arrived at similar results.

Traditionally, the factors used to explain the rate of adoption and the long run equilibrium level of use of new agricultural technology as identified in the economic literature include: credit constraints, risk aversion, the farmer's landholding size, land tenure system, human capital endowment, quality and quantity of farm equipment, and supply of complementary inputs (Feder, Just & Zilberman, 1985; Griliches, 1957). Among the studies that have adopted this approach are Makokha *et al.* (2001), Ouma *et al.* (2002), and Wekesa *et al.* (2003). Makokha *et al*. (2001) studied determinant of adoption of fertilizer and manure in Kiambu District, focusing on soil quality as reported by the farmers. They found high cost of labour and other inputs, unavailability of demanded packages and untimely supply as the main constraints to fertilizer adoption. Ouma *et al*. (2002) also focused on adoption of fertilizer and hybrid seed in Embu District and found that agro-climate, manure use, cost of hired labour, gender of the farmer and access to extension services were important determinants of adoption. Wekesa *et al.* (2003), in addition, surveyed adoption of improved maize sorts and fertilizer in the coastal lowlands of Kenya and observed that flawed climatic conditions, high cost and unavailability of seed, perceived soil fertility and low financial endowments had been responsible for the low adoption. These studies have three core limitations: they are based on cross-sectional data, they cover smaller geographical areas that cannot precisely mirror the diversity among farming communities and they use ordinary binary probit or logit which pay no attention to the inter-dependence of agricultural technologies. Their results are, thus, probable to suffer endogeneity bias.

Malik *et al.* (1992) studied the role of education in the adoption of weedicides for wheat crop by farmers in Gojra Tehsil. Using 10 randomly selected villages, 150 farmers were drawn at random and interview schedule was the main instrument used in the instrument for data collection. According to the research, weeds impose heavy losses on wheat production in Gojra Tehsil and therefore immediate strategies were demanded to curb the damage. The result drawn from the research revealed that education is very significant in the adoption and application of almost all the important weedicides in the study area. Their study lacked rigors econometric approach, did not address the measurement error in dependency, is fairly old and may not accurately reflect the current situation.

A study by Olwande, Sikei and Mathenge (2009) used panel data to observe determinants of fertilizer adoption and intensity of use. Using a double-hurdle model, they determined that age and schooling of the farmer, access to credit, presence of a cash crop, distance to fertilizer market and agro-ecological potential stimulus the chance of fertilizer adoption. A double-hurdle model is beneficial in capturing intensity of adoption but it ignores the reality that adoption of fertilizer may also be influenced by related practices such as adoption of improved maize seed. The dependency ratio is also another problem of this study and has been the problem of many studies due to the way it has been captured. Using age as a measure of dependency in developing nations would lead to biase and inconsistent results because many children (12 - 17 years) are the bread winners of their households.

2.3Research Gap

In general, the adoption studies had some limitations in their analyses and, thus, did not adequately explain farmers' adoption decisions. Some of these studies had methodological limitations, as they simply used a linear regression model, ordinary binary probit or logit to analyze the adoption behaviour of farmers (Kebede *et al.*, 1990); and some had data limitation, as they used intended (planned) adoption for some of sample farmers as the dependent variable (Aklilu, 1980). These factors do not make it possible for detailed analysis of the observed diversity among farming communities and also do not pay attention to the inter-dependence among agricultural technologies. Their results are, thus, likely to suffer endogeneity bias.

III. METHODOLOGY

3.1Area of study

The study was carried out in the Northern Region of Ghana, specifically in Tamale Metropolitan, Savelugu-Nanton, and West Mamprusi district. These districts have the characteristics of all the other districts in the Northern Region. Tamale Metropolitan, Savelugu-Nanton and West Mamprusi are located between Latitude 9°24′30.1″N 0°50′25.63″W, 9°24′N 0°28′W and 10°21′N 0°46′W respectively. The Greenwich Meridian passes through a number of human settlements around the catchment area. The districts cover a land area of 731, 1790.7 and 4892 kilometers square respectively. The vegetation consists of the districts are predominantly grassland, and greater part of it is under arable crop cultivation. The main occupation of the people is farming, with maize, groundnut, vegetables, and cowpea as the common crops. Between January and March is the dry season. The wet season is between about July and December with an average annual rainfall of 750 to 1050 mm (30 to 40 inches). The highest temperatures are reached at the end of the dry season, the lowest in December and January. Rainfall is seasonal and erratic. However, the hot Harmattan winds from the Sahara blows frequently between December and the beginning of February. The temperatures can vary between 14 °C (59 °F) at night and 40 °C (104 °F) during the day.

3.2 Source of Data

This study draws upon data from the farmer survey of the Innovation for Poverty Action (IPA). Being designed to be a regionally representative, multi-purpose rural household and village surveys, the farmer survey was first collected in 2009 and subsequently waves were conducted in 2010 and 2011. The survey was divided into several components (drawing of sample frame from GLSS+, experiment, and household questionnaire) and collects detailed farmer and household data spread across various towns/villages in the Northern region of Ghana.

In year one, after the first sample frame has been drown, two experiments were conducted. The first was a 2x2 experiment: maize farmers either received (a) a cash grant or no cash grant, and (b) a rainfall insurance grant or no rainfall insurance grant. In the second experiment, to a separate group of farmers, rainfall insurance was sold at prices ranging from one eighth of actuarially fair to market price (i.e., actuarially far plus a market premium to cover servicing costs). In year two, another cash grant experiment was conducted, but only offered rainfall insurance for sale (again, at randomly different prices) rather than giving some out for free as in year one. In year three, only the insurance pricing experiment was conducted.

The comprehensive farmer survey in the various waves included many components: household socioeconomic indicators (including education, health, waged labour, and formal employment), plot-level farming questions (including land tenure, seeds, chemical inputs, agricultural labour, harvest, crop sales and storage), livestock, fishing, agricultural processing, household assets, expenditures, consumption, social networks, insurance knowledge, risk perceptions and finance (including borrowing, lending, savings, other income, and transfers). The number of sample farmer households and the panel formed for the analysis of the vulnerability to poverty in the Northern region of Ghana is show in the Table 1.

Table 1: Yearly Distribution of sampled maize farmers

Years	Sample	Panel
2009	1,088	576
2010	1,117	576
2011	1,143	576

Source: Author's own calculations (2020) based on 2009, 2010, 2011 EUI data

3.2.1Methods and model

There are two main binary choice panel data estimators in the literature. One applicable binary choice panel data estimator is the fixed effects logit model (Cameron & Trivedi, 2009). This model is based on a within transformation (which also drops any time invariant observable variables in x_{it}) and is also based on variation in the dependent variable over time (which limits the number of observations to be used for estimation and consequently reduces our sample size significantly). Random effects probit model, on the other hand, assists in controlling for unobserved heterogeneity when this heterogeneity is constant over time and correlated with independent variables. This study however prefers the random-effects probit model over the fixed effects logit model.

Using a random effects probit framework, the farmers' decision to adopt weedicide was modeled for households in Northern region of Ghana. Let the latent model of weedicide adoption be specified as:

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$$m_{it}^* = x_{it}^{'}\beta + \varepsilon_{it} \qquad i = 1,2,...,N; \quad t = 1,2,...,T \qquad (1)$$

$$\varepsilon_{it} = \alpha_i + u_{it} \qquad (2)$$

where m_{it}^* is a latent dependent variable; m_{it}^* is the observed binary outcome variable defined as:

$$m_{it}^* = \begin{cases} 1 & \text{if } m_{it}^* > 0; \\ 0, & \text{otherwise} \end{cases} \qquad (3)$$

x_{it} represents a vector of time-varying and time-invariant exogenous variables which influence m_{it}^*; β represents a vector of parameters to be estimated; ε_{it} is a composite error term which can be decomposed into α_i, a term capturing unobserved individual (household in our case) heterogeneity, and $u_{it} \sim IN(0, \sigma_u^2)$ a random error term. The subscripts *i* and *t* refer to households and time periods respectively. One can marginalize the likelihood function by assuming that, conditional on the x_{it}, the unobserved individual heterogeneity term $\alpha_i \sim IN(0, \sigma_u^2)$, is independent of the x_{it} and u_{it}.

Assuming that the distribution of the latent variable m_{it}^*, conditioned on α_i, is independent normal (Heckman, 1981), the vector of parameters, i.e, the β's can be estimated easily.Thus,

$$\Pr(m_{it} = 1 | \alpha_i, x_{it}) = \Pr\left(\frac{u_{it}}{\sigma_u} > \frac{-x_{it}^{'}\beta - \alpha_i}{\sigma_u}\right) = \Phi(v_{it}) \qquad (4)$$

where

$$v_{it} = -\left(x_{it}^{'} + \alpha_i\right) / \sigma_u \qquad (5)$$

and Φ is the distribution function of the standard normal variate. Consequently, the likelihood function to be maximized (which is marginalized with respect to *α*) is given by:

$$\prod_i \left\{ \int_{-\infty}^{\infty} \prod_{t=1}^{T} \left[1 - \Phi\left(x_{it}^{'}\beta^* + \sqrt{\frac{\lambda}{1-\lambda}}\alpha^* \right) \right]^{1-m_{it}} \times \left[\Phi\left(x_{it}^{'}\beta^* + \sqrt{\frac{\lambda}{1-\lambda}}\alpha^* \right) \right]^{m_{it}} \phi(\alpha^*) d\alpha^* \right\}$$

where $\beta^* = \beta / \sigma_u$ and $\alpha^* = \alpha / \sigma_u$. Standard software can be used to estimate β^* and *λ*, which are normalized on σ_u

Table 2: Description, Measurement and a priori Expectation of Variables

Variables	Description	Measurement	Expected sign
Hadopt	Weedicide adoption	Yes =1; No = 0	
Sex	Gender	Male =1; Female = 0	+
Agehh	Age of the household head	The actual number of years of the household head	+
Mstatus	Marital status	Married =1; any other =0	+
Eduhh	Educational level of the household head	Years spent in schooling	+
Hhsize	Household size	Total number of members of the household	-
Depdcr	Dependency ratio	Ratio of non-income earning members of the household to income earning members of the household	-
Farmsize	Farm size	The area of land under maize cultivation in acres	+
Hprice	Price of Weedicide	Market price of 1 liter of Weedicide	-
Lprice	Price of labour	Hiring pay of farm labour per man-day for weeding	+
Fnpk	Fertilizer NPK	Yes =1; No = 0	+
Forg	Other type of inorganic fertilizer used	Yes =1; No = 0	+
Snetwk	Nnoboa (communal labour)	Number of people in the group	-
FarmY	Farm income	Amount in Ghana cedis	+

Source: Author's construction

From the theoretical and empirical literature review, equation (6) will be the empirical model to be estimated. In the model, the study postulate that the probability of adopting weedicide is influenced by the Sex of the household head (sex), the age of the household head (Agehh), marital status of the household head (Mstatus), educational level of the household head (Eduhh), household size (Hhsize), dependency ratio (Depdcr), farm size (Farmsize), price of Weedicide (Hprice), price of labour (Lprice), hired labour (Hirelab), NPK fertilizer (Fnpk), any other type of inorganic fertilizer (Forg), social network by communal labour (SnetwkCL), and total farm income (FarmY). The full regression equation is shown below:

$$\begin{aligned} Hadopt = {} & \beta_0 + \beta_1 sex_{it} + \beta_2 Agehh_{it} + \beta_3 Mstatus + \beta_4 Eduhh_{it} + \beta_5 Hhsize_{it} \\ & + \beta_6 Depdcr_{it} + \beta_7 Farmsize_{it} + \beta_8 Hprice_{it} + \beta_9 Lprice_{it} + \beta_{10} Fnpk_{it} \\ & + \beta_{11} Forg_{it} + \beta_{12} Snetwk_{it} + \beta_{13} FarmY_{it} + \varepsilon_{it} \end{aligned} \tag{6}$$

The description of the variables, measurement and the aprior expectation of the variables in equation (6) are given in Table 2.

IV. RESULTS AND DISCUSSIONS

Descriptive statistics

In Table 3, it is evident that 41.84 percent of the 576 farm households interviewed in 2009 adopted weedicide, whereas the remaining majority (58.16%) were non-adopters. In 2010, the number of weedicide adopters increased to 54.86 percent but the percentage of the non-adopters among the same number of households (576) interviewed decreased to 45.14 percent. It is more interesting to see the percentage of weedicide adopter reaching 77.08 percent which was 84.23 percent increase in the initial number of weedicide adopters among 576 maize farm household with two years. Within the same time frame (2 years), the number of weedicide non-adopters decreased from 335 to 132 which is about 60.60 percent. In total, 1001 farm household adopted weedicide and 727 household were non-adopters as shown in Table 3. Having followed the same respondents for three cropping years, it is evident that weedicide adoption by farm households kept increasing while non-adoption of weedicide constantly decreased from one cropping year to the other. *The question now is "what factors drive the adoption of weedicide by farm households in the Northern region of Ghana?"*

Table 3: Balance Panel Members in each Wave

Statues	Year			
	2009	2010	2011	Total
Adopter	241 (41.84%)	316(54.86%)	444(77.08%)	1,001
Non-adopter	335(58.16%)	260(45.14%)	132(22.92%)	727
Total	576	576	576	1,728

Source: Author's own calculations based on 2009, 2010, 2011 EUI data

The sample contains 98.15 percent of the farm households heads were male and only 1.85 percent were female. Figure 1 presents a detailed illustration of gender composition of heads of peasant households and their decision to adopt or non-adopt weedicide. It was revealed that majority (59.4%) of the females included in the study was non-adopters of weedicide and the other hand majority (58.3%) of the males included was adopters. This distribution is not surprising because men are the heads of households in a typical Northern region of Ghana cultural setting. It is therefore expected that males were more likely to adopt weedicide than females. *The unanswered question is by how much are males more likely to adopt weedicide than females?*

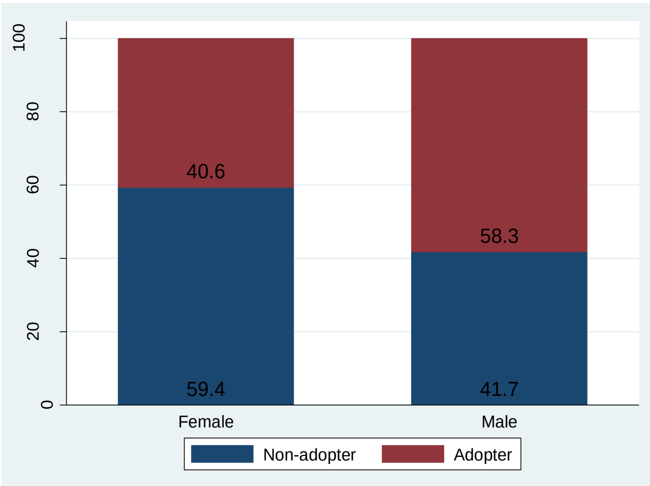

Figure 1: Distribution of Adopters of Weedicide across the Gender of Household Head

Source: Author's own calculations based on 2009, 2010, 2011 EUI data

Figure 2 presents distribution of adopters and non-adopters of weedicide across the marital status of the household head. It can be observed from the Figure 2 that majority (58.7%) of the household head who are married adopted weedicide and the remaining 41.3 percent were non-adopters. From the never married household heads, 50.5 percent were adopters while 49.5 remained non-adopters. It was also revealed that about 67 percent of the household heads were separated being adopters, 46.7 percent of the widowed were also adopters while 100 percent of the divorced household heads being non-adopters of weedicide.

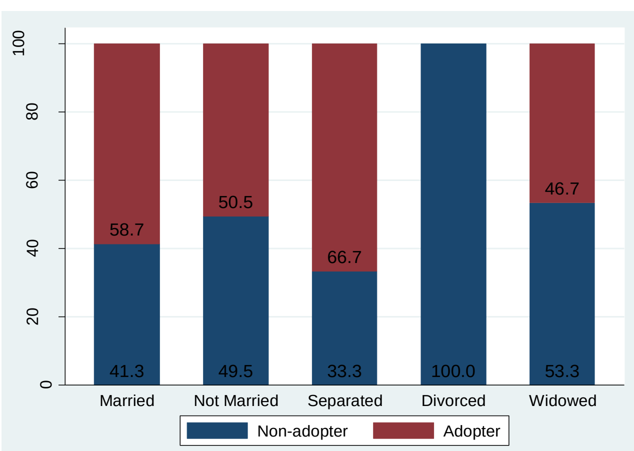

Figure 2: Distribution of Adopters across the Marital Status of the Household Head

Source: Author's own calculations based on 2009, 2010, 2011 EUI data

Table 4 presents the test results of the use of agro-chemicals among the farm households included in this study for statistical differences between the two groups (adopters and non-adopters), using t-tests of differences in means across groups. Three out of the 5 chemicals were statistically significantly different.

Table 4: Agro-Chemical and Weedicide Adoption

Variables	All Households	Adopting Households	Non-adopting Households	Mean Difference	t-value
	Percentage	Percentage	Percentage		
NPK Fertilizer	70.313%	72.83%	66.85%	-5.98%***	-2.6888
Fertilizer Ammonia	58.33%	62.64%	52.41%	-10.23%***	-4.2784
Other inorganic Fertilizer	6.54%	9.39%	2.61%	-6.78%***	-5.6746
Insecticide	3.24%	3.80%	2.48%	-1.32%	-1.5302
Fungicide	0.29%	0.40%	0.14%	-0.26%	-1.0009
Observations	1728	1001	727		

Source: Author's own calculations based on 2009, 2010, 2011 EUI data

*, ** and ***denotes significance at the 10%, 5% and 1% levels respectively

From Table 4, it can be observed that along all lines of agro-chemicals used, in all 70.31 percent of the household used NPK fertilizer, followed by Ammonia fertilizer, 6.54 percent other inorganic fertilizer, 3.24 percent insecticide and 0.29 percent in fungicide. It is quite clear that the most used agro-chemical among maize farmers in the Northern region of Ghana is NPK fertilizer and the fungicide being the last used agro-chemical. This follows the normally maize farming practices where more NPK fertilizers are needed to boost yield with little difficult in dealing with fungi. It was also found that weedicide non-adoption households recorded lower (compared to the weedicide adoption households) percentage along all types of agro-chemical listed in the study.

Even though there are differences in all the percentage of households that used agro-chemical between adopted and non-adopted households, only three (3) of the difference was significant. Interestingly, all the three were different types of fertilizers and also significant at 1 percent. Fertilizer basically provides nutrients to the soil which enable plants and weeds to grow faster. There is therefore the need to weed the farm constantly and the more efficient and timely way of doing this is through the application of weedicide. Table 5 presents the statistical differences of all the remaining outcome variables of the determinants of weedicide adoption.

Table 5: Descriptive Statistics of Adopters and Non-adopters of Weedicide

Variables	All Households		Adopting Households		Non-adopting Households		Difference		t-value
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	
Age	45.025	15.025	44.956	14.621	45.120	15.573	0.164	0.952	0.223
Years of Schooling	2.287	5.238	2.381	5.468	2.158	4.904	-0.222	-0.564	-0.871
Household size	7.565	3.272	7.676	3.272	7.411	3.268	-0.265*	-0.004	-1.663
Dependency ratio	3.881	2.501	3.800	2.404	3.993	2.628	0.193	0.224	1.582
Total Farm income	570.417	1,024.2	641.137	1,091.445	473.042	915.455	-168.10***	-175.99	-3.378
Farm size	10.313	17.215	11.159	20.702	9.151	10.598	-2.008**	-10.104	-2.397
Price of Labour	7.888	18.611	8.775	19.528	6.667	17.208	-2.108**	-2.32	-2.327
Price of Weedicide	27.24	12.084	20.924	12.524	35.938	0.755	15.014***	-11.769	32.280
Nnoboa	5.379	6.968	4.858	6.951	6.096	6.932	1.238***	-0.019	3.660
Observations	1728		1001		727				

Source: Author's own calculations based on 2009, 2010, 2011 EUI data

*, ** and ***denotes significance at the 10%, 5% and 1% levels respectively

From Table 5, the mean household size of all household stood at 8 members with a standard deviation of 3 members. However, the average household size of the adopters of weedicide was a little higher (8 members) than that of the non-adopters (7 members). It was further noticed that the mean household size of the adopters and the non-adopters is significantly different at 10 percent significant level. Even though there is a significant difference between the means, this difference cannot be meaningful since the standard deviation difference is very small.

The mean total farm income of the adopters differs significantly from that of the mean of the non-adopters. It is noticed that there is a meaningful 1 percent significance difference in the means of farm income of the adopters and non-adopters. This difference is very meaningful since the standard deviation difference is large (GHC 175.99) and also very big difference in average farm income (GHC 168.10) among the groups. It is evident in Table 5 that the average farm size of weedicide adopters differs significantly from the average farm size of the non-adopters. The difference is significant at 5 percent and also statistically and economically meaningful.

Also, there is a 5 percent significant and a meaningful difference in the means of price paid to labour by farm households who adopt weedicide and the non-adopted farm households. There is a significant difference in the average price of weedicide known by the adopter farm household and the non-adopter farm households. The mean number of communal labour (nnoboa) on who visits the adopter's farm differs significantly from the mean number of communal labour who work with the non-adopters.

Regression analysis

Tables 6 displays the marginal effects for determinants of weedicide adoption among maize farmers in the Northern region of Ghana as presented in equation (6). The diagnostic statistics of the results from the IVprobit estimation revealed [thus, *rho* = - 4.43] the absence of correlation between the error terms and adoption of weedicide. Also, Sigma (1.164) shows that the variance of the reduced-form equation for the endogenous regressor is insignificant. This implies absence of selection bias in the sample. The insignificance of the wald test of endogeneity or *rho* being equal to zero is equivalent to saying that the variable suspected to be endogenous is actually exogenous. In other words, if the estimated *rho* is insignificant, then we cannot reject the null that there is no endogeneity issue and a plain probit regression could be used.

The coefficient of *rho*, which indicates the important role of unobserved heterogeneity, is statistically different from zero in both the random effects and correlated random-effects probit models. This clearly indicates the need to use panel data models in estimating the weedicide adoption model. The result from the correlated random-effect was therefore considered to be the best and was referred to in the discussion.

The estimated result from correlated random-effects probit model indicates a statistically significant model with wald $X^2(13)$ =163.84 and likelihood-ratio $X^2(01)$ = 3.48 both significant at 1 percent and 5 percent respectively. This suggests that the independent variables (as a group) discriminate well between weedicide adoption farm households and others. However, only seven of the variables (regressors) were significant. The significant variables are dependency ratio, farm income, the use of NPK fertilizer, the use of other inorganic fertilizer, price of labour, price of weedicide and social network (number of members in his or her nnoboa group). The signs of the variables also agreed with *a priori* expectations or direction of effect on agricultural technology adoption.

Table 6: Determinants of weedicide adoption

Variables	Random effects probit		Correlated random effects probit		IVprobit	
	Coeff.	dy/dx	Coeff.	dy/dx	Coeff.	dy/dx
Gender	0.6028 (0.520)	0.1272 (0.146)	0.5157 (0.009)	0.1028 (0.134)	0.4994 (0.2868)	0.1196 (0.1315)
Age	0.0008 (0.004)	0.0001 (0.001)	-0.0004 (0.004)	-0.0001 (0.001)	0.0048 (0.0045)	0.0010 (0.0011)
Married	0.1358 (0.227)	0.0213 (0.039)	0.0621 (0.224)	0.0092 (0.035)	0.0634 (0.1912)	0.0135 (0.0409)
Years of education	0.0048 (0.010)	0.0007 (0.001)	0.0054 (0.010)	0.0008 (0.001)	0.0068 (0.0088)	0.0014 (0.002)
Household size	0.0470 (0.029)	0.0068 (0.004)	0.0439 (0.029)	0.0063 (0.004)	0.0239 (0.0297)	0.0049 (0.0055)
Dependency ratio	-0.0919*** (0.036)	-0.0133** (0.006)	-0.0918*** (0.036)	-0.0131** (0.006)	-0.0841*** (0.0302)	-0.0173** (0.0072)
Farm income	0.1503*** (0.042)	0.0217*** (0.007)	0.1535*** (0.042)	0.0219*** (0.007)	0.4994* (0.287)	0.1028 (0.0868)
NPK Fertilizer	0.2644** (0.115)	0.0414** (0.020)	0.2532** (0.114)	0.0391** (0.020)	0.1080 (0.1460)	0.0228 (0.0275)
Other inorganic Fertilizer	1.1538*** (0.228)	0.0832*** (0.021)	1.0966*** (0.225)	0.0806*** (0.0202)	0.8906*** (0.2826)	0.1146*** (0.0360)
Price of labour	0.0354* (0.021)	0.0051* (0.003)	0.0344* (0.021)	0.0049* (0.003)	0.0179 (0.0227)	0.0037 (0.0041)
Price of weedicide	-3.8997*** (0.333)	-0.563*** (0.075)	-3.9260*** (0.334)	-0.5610*** (0.075)	-3.1000*** (0.6896)	-0.638*** (0.0512)
Social network (Nnoboa)	-0.0115 (0.007)	-0.0017 (0.001)	-0.0149** (0.008)	-0.0021* (0.001)	-0.0099* (0.0060)	-0.0020 (0.0014)
Farm size	0.0019 (0.063)	0.0003 (0.009)	-0.0147 (0.062)	-0.0021 (0.009)	-0.0782 (0.0722)	-0.0161 (0.0182)
Constant	11.6804*** (1.249)		8.8804** (3.915)		7.3459** (3.6879)	
Number of observation	1409		1409		1405	
Number of groups	554		554			
Log likelihood	-548.558		-538.616		-2757.284	
Wald chi2 (13)	156.47***		163.84***		366.73***	
Rho	0.159* (0.0858)		0.159* (0.0858)		- 4.43 (0.3629)	
Sigma	0.453 (0.1395)		0.4351 (0.1395)		1.1645** (0.0220)	
Likelihood-ratio test chibar2 (01)	5.97***		3.48**			
Wald test of exogeneity: chi2(1)					1.11	
Prob > chi2					0.2917	

Source: Author's own calculations based on 2009, 2010, 2011 EUI data

*, ** and ***denotes significance at the 10%, 5% and 1% levels respectively

It is evident from Table 6 that other factors held constant, a unit increase in the dependency ratio decreases the adoption of weedicide by 1.31 percent. Adeoti (2009) and Ouma, Bett and Mbataru (2014) corroborate the results on the effect of dependency ratio on weedicide adoption. The possible explanation for this trend are that; increase in the number of non-working household members as compared to those working infers higher free labour availability for productive farm activities specially weeds control. This apparently discouraged weedicide adoption but encourage hand weeding since there is available labour. Also, increase in the number of dependents in the household may reduce the household income available for investments, thus discouraging weedicide adoption. Owing to this, farm households with lesser dependency ratio tend to be more likely to adopted weedicide than a higher dependency ratio farm household. On the contrary, Obasoro, Iwinlade, Popoola and Adeoti (2015) study on effect of adoption of improved soybean variety on productivity of farm households in Benue State, Nigeria, and found a positive relationship between dependency ratio and adoption of improved soybean variety.

The reported marginal effect indicates that a unit increase in farm income increases the probability of weedicide adoption by 2.19 percent. Indeed, availability of income is essential in the purchase of production inputs, improves access to land

and adoption of innovations and hence improved productivity. This suggests that farmers with higher farm income can afford to adopt any farm technology that enhances their production and also make farming activity less stressful. This finding reinforces earlier findings (Gillespie *et al*., 2007; Samiee *et al*., 2009; Larbi, 2015) on the importance of farm income in enabling farm households to adopt improved agricultural technology and make a transition to a better method of farm management. It can therefore be concluded that the higher the farm income the greater the likelihood of farm household adopting weedicide.

Farm households which used NPK fertilizer have about 3.91 percent higher probability of adopting weedicide compared to farm households which did not use NPK fertilizer. Again, farm households which used other type of inorganic fertilizer have about 8.06 percent higher probability of using weedicide. This could probably be explained by the persistent growth of weeds due to availability nutrients (constant provided by the applied inorganic fertilizer) and relative level of awareness about the implications of using agro-chemicals on a farm. Our findings is in agreement with Ogada *et al*., (2014) work on the simultaneous estimation of inorganic fertilizer and improved maize variety adoption decisions in Kenya.

The marginal effect results in Table 6 have indicated that there is a marginal increase in the propensity to adopt weedicide as the price paid for weeding increases. An increase in the price of labour by GHC 1 will cause about 0.49 percent increase in the probability of adopting weedicide. A critical examination of the data shows that there is a significant difference between the price paid to labour by adopters and non-adopters of weedicide. From Table 5, it was clear that the adopters of weedicide paid slightly higher labour price than non-adopters. This could have been the possible explanation to the relationship between price paid to labour for weeding and adoption of weedicide. Larbi (2015) studied the factors influencing IPM adoption in Ghana and found labour cost to have a significant positive relationship with IPM adoption. Our results is in line with that of Larbi (2015) findings.

Price of weedicide on the other hand serves as the price of the good and therefore has to be negatively related to the demand or the use of the good. It is obvious from the marginal effect that, other factors held constant, a unit increase in the price of weedicide reduces adoption by 56.10 percent. This indicate the critical role that reduction in the price of weedicide plays in the promotion of weedicide adoption in Ghana.

Table 6 show that the probability of a farm household adopting weedicide decreases by 0.21 percent if the association of communal labour increases by one member. Detailed investigation of the difference sections (Table 5) of our panel data indicates that there is significant differences in the number of members in the assocation of communal labour that the adopter and the non-adopter of weedicide belong to. It was also shown that the membership is higher for the non-adopters and therefore justified to have not adopted the weedicide for the possible reason that they have enough enough labour to weed their farms and hence no need for weedicide. This is confirmed in the study of Uwagboe *et al*., (2012), Tewodaj *et al*., (2009), and Hailu *et al*., (2014).

V. CONCLUSION AND RECOMMENDATIONS

This paper investigated the determinants of weedicide adoption among maize farmers in the Northern region of Ghana. To test for the robustness of the different correlates of weedicide adoption, three alternative nonlinear specifications called random effects probit, correlated random effects probit and IVprobit were estimated. The diagnostic statistics of the results from the IVprobit estimation indicated the absence of correlation between the error terms and the quantity of maize sold and hence no endogeneity issue. This suggests that any plain probit regression could be used. Since the correlated random-effects probit model is better than plain probit, the results of the correlated random-effects probit model was referred to in the course of discussion of the result.

It was found that economic dependency ratio, farm income, the use of NPK fertilizer, other inorganic fertilizer, price of labour, price of weedicide and social network (number of members in his or her nnoboa group) were all good determinants of weedicide adoption. More specifically, dependency ratio, price of weedicide and social network (number of members in his or her nnoboa group) were negatively related to weedicide adoption whereas farm income, the use of NPK fertilizer, other inorganic fertilizer, and price of labour positively related to weedicide adoption.

Given the above findings, this study recommends the following policy to the stakeholders of the agricultural sector with kind interest on maize production.

1. All the stakeholders of agriculture have to take pragmatic steps to reduce the dependency ratio in peasant farm household. For instance;
   a. Government should create more jobs (agricultural or non-agricultural related) in the rural areas for the youth as well as retired workers.
   b. The Sports Ministry should create sports academies in the rural areas.
   c. Ministry of Health through the PPAG should continue or intensify their crusade on birth control.
2. Policy makers in the Ministry of Food and Agriculture, therefore, ought to formulate and implement policies that promote package adoption of agricultural inputs (fertilizer and weedicide). Thus,
   a. Provision of price support for all elements of a technology package (fertilizer and weedicide) at the same time.
   b. Encouragement of agricultural chemical producers or dealers to jointly sell inorganic fertilizer and weedicide so that it is clear to the peasant farmer that optimal results are realizable only with complete package adoption. This can be done through “buy one

get one free" (buy one bag of fertilizer and get one weedicide for free) sort of promo.

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