The Determinants of Farmer Adoption of Improved Peanut Varieties and Their Impact on Farm Income: Evidence from Northern Ghana.

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Abstract

This study employed the Heckman Two-stage model to identify the determinants of the adoption of improved peanut varieties and examine their potential impact on farmers' in Savelugu-Nanton and Tolon-Kumbungu districts in the Northern Region of Ghana. A cross-sectional data of 219 peanut farmers from the two districts were used in the analysis. The estimated results indicate that membership in a farm organization, number of bicycles owned, importance of early maturity as a varietal characteristic, and farm location significantly influence the adoption of improved peanut varieties. Also, the estimated ordinary least squares (OLS) part or the second step of the Heckman model suggest how peanut acreage, number of bicycles owned, and the dependency ratio could influence the income from farming as a result of improved variety adoption.

JEL classification:
Key words: peanut variety, technology adoption, Ghana, Heckman two-stage model

Introduction

Agriculture continues to be a major contributor to the growth of the Ghanaian economy. The sector's contribution to gross domestic product (GDP) was 30.2 percent in 2010 (MoFA, 2011). Agriculture's contribution to employment is 50.6%. The sector is dominated by smallholder farms. About 90 percent of farms are less than 5 acres in Ghana. More than one-half (56.2 percent) of the nation's population lives in rural areas. Despite the prominent role of agriculture in Ghana, poverty levels are high in rural areas, especially among small scale farmers.

The adoption of high-yielding-varieties (HYV) of crops by farmers in developing countries has been viewed as the solution to lower incomes in agriculture over the years (Besley and Case, 1993). As a result, many donor countries through their international development agencies and in cooperation with international research centers have invested substantial resources in agricultural technologies in developing countries. However, most of the new agricultural technologies have not fully achieved the desired goals (e.g., high rate of adoption (Faltermeier and Abdulai, 2009)). This observation has, therefore, spawned numerous studies about agricultural technology adoption related issues and their impact on poverty in developing countries in recent years (Besley and Case, 1993; Doss and Morris, 2001; Mendola, 2007, Becerril and Abdulai, 2009). Results of these studies suggest that adoption decisions are based on risk, uncertainty, input rationing, information imperfections, human capital and social networks (Just and Zilberman, 1988; Smale et al., 1994; Sadoulet and de Janvry, 1995; Koundouri et al., 2006; Becerril and Abdulai, 2009; Uaeieni et al., 2009).

Technology adoption has a direct effect on the farmer's income, usually resulting from higher yields, higher prices, or both. Yield improving technologies usually involve bundling of improved seeds with appropriate fertilizer, pesticide and fungicide applications. According Karanja et al. (2003), if farmers fail to adopt the package higher outputs may not be realized.

Agriculture technology adoption literature suggests that most studies have addressed the impact of technology on income from a macro perspective. Most of the recent studies that have taken a micro view, however, have generally used farm household level data (Karanja et al., 2003; Mojo et al., 2007; Mendola, 2007; Becerril and Abdulai, 2009; Kassie et al., 2010; Simtowe et al., 2010). Our study is different because we are using data collected at the farmer and not household level.

In Ghana, although improved peanut varieties have been available for decades, complete adoption has not, so far, been achieved. For example, Mani Pintar, and Shitaochi (commonly known as Chinese or China), F-mix and ICGS 114 (Sinkarzei) were released in 1960, 1970s, 1985, and 1988, respectively (Atuahene-Amankwa et al., 1990). The Savanna Agricultural Research Institute (SARI), in collaboration with its partners, has developed and disseminated other improved peanut varieties in northern Ghana in recent years. To our surprise, Chinese and

Mani Pintar still appear to be popular among farmers in the research area (see Table 2). This finding is similar to what Atuahene-Amankwa et al. (1990) observed in the late 1980s.

This study contributes to the literature by empirically identifying the determinants of improved peanut varieties (IPV) adoption and how they may impact farmers' income in Northern Ghana. We apply the Heckman two-stage procedure to address self-selection problems in non-experimental data. By addressing the relationship between adopters and non-adopters, we are addressing the selection bias.

Peanuts in Ghana

Ghana is one of the leading producers of peanuts in the world (see Table 1). Ghana ranked 10th (530,887 MT of in-shell peanuts) in production volume in the world and 4th in Africa, right behind Nigeria, Senegal and Sudan (FAOSTAT, 2011). The peanut is the most important legume crop grown in Ghana in terms of the total production and value (Tsibey et al., 2003). Agro-ecologically, peanuts are grown mostly in the northern savanna zone, which is conducive for peanut production. The zone receives an average of 43.31 inches of rain per annum. Ministry of Food and Agriculture (MOFA, 2011) reports show that farm yields of peanuts are considerably below the achievable levels (2.50 MT/Ha). The Northern region recorded the highest yield of 1.92 MT/Ha in 2010. Peanuts are commonly grown alongside major crops such as maize, yams and millet (Tsibey et al., 2003). The 2010 agricultural production figures show that the Northern Region (227,650 MT) and Upper West (196,676 MT) produced about 80 percent of the nation's total peanut production (MOFA, 2011). Almost all peanuts produced in Ghana are consumed domestically. The export market is almost non-existent with aflatoxin contamination being the major constraint for peanut exports to Europe and America (Awuah et al., 2009; Pazderka and Emmott, 2010).

Like the rest of Sub-Saharan Africa, the peanut is a valuable cash crop in Northern Ghana and a food staple for millions of Ghanaians (MoFA, 2011). Peanuts are high in edible oil, protein, essential vitamins and minerals. Peanuts are also processed into paste (butter) and widely used by Ghanaians to make soup, stews, and cereal mixtures (Asibuo et al, 2008). In the Northern Region, women process the meal into cakes which are consumed as snacks (kulikuli) or further processed into powdered form (kulikuli zim). Peanut cake from industrial oil processing is mostly used to feed poultry and livestock, especially in the south (Goldworthy and Fisher, 1987; Awuah et al., 2009).

Theoretical Model and Empirical Specification

Given that the focus of this study is to identify the determinants of the adoption of improved peanut seeds and how such adoption may affect income from farming, we state the basic relationship of the impact of the new technology adoption on farm income, measured by farmer's farm income as a linear function of vector of explanatory variables (X_i) and an adoption dummy variable (W_i). The linear regression can be specified as

$$Y_i = X_i^{'}\beta + \delta W_i + \mu_i \qquad 1$$

where Y_i is the mean farmer income from farming, μ_i is a normal random distribution term, and W_i is a dummy variable for use of new technology; $W_i = 1$ if the technology is adopted and $W_i = 0$ otherwise. The vector X_i represents household and farm characteristics. Whether farmers adopt improved varieties or not is dependent on the characteristics of farmer, farm and technology. By deciding to adopt an improved seed variety the farmer has self-selected to participate instead of a random assignment.

Following Becerril and Abdulai (2009), we assume that the farmer is risk–neutral. The index function used to estimate the adoption of an IPV can be expressed as:

$$W_i^* = X_i^{'}\gamma + \varepsilon_i \qquad 2$$

where W_i^* is a latent variable denoting the difference between utility from adopting improved varieties U_{iA} and the utility from not adopting the technology U_{iN} . The farmer will adopt the new technology if $W_i^* = U_{iA} - U_{iN} > 0$. The term $X_i^{'}\gamma$ provides an estimate of the difference in utility from adopting the technology ($U_{iA} - U_{iN}$), using the household and farm-level characteristics, X_i , as explanatory variables , while ε_i is an error term. In estimating equations (1) and (2), it needs to be noted that the relationship between the new technology and an outcome such as income could be interdependent. Specifically, the selection bias occurs if unobservable factors influence both error terms of the income equation (μ) and the technology choice equation (ε), thus resulting in the correlation of error terms of the outcome and technology choice specifications. Thus, estimating equation 1 using the ordinary least squares (OLS) will lead to biased estimates. To address this problem, a two-step Heckman's procedure was used to analyze factors affecting the probability of adopting IPV. The model is appropriate because it addresses simultaneity problems.

The Heckman Two-Step Method

The Heckman (1976) two stage procedure has been used to address selection bias when the correlation between the two error terms is greater than zero (Hoffman and Kassouf, 2005; Adeoti, 2009; Johannes et al., 2010; Siziba et al., 2010). The approach depends on the restrictive assumption of normally distributed errors (Wooldridge, 2002).

The procedure involves, first, the estimation of the selection equation using a probit model (adoption equation 2) and second, the estimation of the income equation 1. The adoption equation (equation 2) is estimated as:

$$W_i^* = X_i^{'}\gamma + \varepsilon_i$$

W_i^* is a latent variable representing the propensity of a farmer to adopt IPV. $X_i^{'}$ is the vector of farmer's assets endowment, household characteristics, technology characteristics and location variable that influence adoption decision. The probit model predicts the probability of adoption and also obtains the inverse Mill's ratio (IMR) as shown below:

$$\lambda_i = \frac{\phi(\rho + \gamma X_i)}{\Phi(\rho + \gamma X_i)}$$

where ϕ and Φ are, respectively the standard normal density function and standard normal distribution functions. λ_i is the calculated IMR term to provide OLS selection corrected estimates (Greene, 2003)

Data and Definition of Variables

The cross-sectional data used in the study were obtained from a survey conducted in July and August 2010. The face-to-face interviews were conducted in 13 communities within three districts (Tamale Metropolitan, Savelugu-Nanton and Tolon-Kumbungu) of the Northern Region. A random sample of 251farmers was selected from the 13 communities to ensure full representation. We are, however, using data from Savelugu-Nanton and Tolon-Kumbungu resulting in a total of 219 data points.

In this analysis, "improved peanut variety" is defined as the variety that is not indigenous to Ghana. Three major varieties of peanuts cultivated in the research area. They include "Chinese", "Bugla" and Mani Pintar. This is in direct contrast with Tsibey et al. (2003) findings which implied that only sinkarzei was cultivated in the research area. Bugla is the only local variety still in cultivation. Mani Pintar and Chinese continue to be dominant even though they were introduced over a generation ago. It is not clear why farmers and traders in this part of the country appear not to be able to differentiate varieties. What is, however, clear is that names given varieties are generally descriptive. For example, the Chinese variety is generally referred to as "simbaligu," meaning, small kernel, while bugla means big kernels. Table 2 shows that the most cultivated IPV by the respondents are Chinese (50%) and Mani Pintar (38%). It was difficult to obtain specific names for some varieties, especially the new improved varieties.

Descriptive statistics and explanation of the variables used in the study are provided in Table 3. The farm characteristics incorporated in our models include household demographic composition, farmland area, access to credit and information, farmer's assets and farm location.

It is shown in Table 3 that 89 percent of respondents adopted improved peanut varieties and about 20 percent of the adopters were females. Farmers, on average, had two contacts with the extension officers during the 2009 farming season. The average age of a respondent was 38 years and 45 percent reported being the household head. The average household size was 13 persons. The average peanut cultivated area was about 4 acres, while the average total farmland was 9 acres. Furthermore, 34 percent of the respondents reported having income from off-farm activities. About 54 percent reported hiring farm labor the previous season. 15 percent of the respondents had formal education and 24 percent of the peanut farmers also farmed soybeans.

Table 4 presents results of differences between means of characteristics describing the improved peanut variety adopting and non-adopting farmers. There appear to be a small number of significant differences between adopters and non-adopters of improved peanut varieties. There is however a significant difference in the total farm income between adopter and non-adopters. Overall, only three variables (total farm income, female and number of bicycles owned by the farmer) show significant differences between adopters and non-adopters. The results suggest that the two sub-samples are similar and, therefore, do not have self-selection bias. It should, however, be noted that mean difference comparisons may not take into consideration other characteristics of the farmer which may compound the impact of adoption on the farmer's income with the influence of other characteristics (Kuhlgatz and Abdulai, 2010).

Empirical Results

Determinants of the probability of adopting IPV

Results for the first stage Heckman probit model are shown in columns 2 and 3 in table 6. Four variables are significantly explained the probability to adopt IPV: membership in a farmer organization (MEMBERSHIP), number of bicycles owned (BICYCLES), early maturity considered important or very important (EARLY MATURITY) and the location of the farmer (TOLON_KUMBUNGU DIST). The membership in farmer organization was positively related to the probability to adopt IPV implying that farmers who belong to a farmer organization or group are more likely to adopt IPV. Farmers who owned bicycles were less likely to adopt an IPV. Farmers who consider early maturing characteristic of peanut varieties to be important or very important, are more likely than those who consider it not be important to adopt IPV. TOLON_KUMBUNGU DIST variable is negatively related to the adoption of an IPV. This means that a farmer located in the Tolon-Kumbungu district is less likely to adopt an IPV compared with a farmer located in the Savelugu-Nanton district.

For comparison purposes, Table 5 reports the results of a conventional probit model which shows that MEMBERSHIP, area under peanut cultivation (PNUTACRES), Early MATURITY and TOLON_KUMBUNGU are factors that determine adoption of improved varieties of peanut. The marginal effects, reported in Table 5 show that the probability of a farmer adopting an IPV increases by 7% if a farmer belongs to a farmer organization. PNUTACRES, the acreage under peanut cultivation, appears to have a negative influence on the adoption of IPV. This means that increasing the acreage under peanut cultivation reduces the probability of the farmer adopting the improved variety, but the decrease is negligible for small farmers. The probability decreases by 1% for every additional acre added to peanut cultivation.

The Outcome Regression

Results for the second stage (OLS) of the Heckman two-step model are shown in columns 4 and 5 of Table 3. The dependent variable is the log of the income from farming. The extension visit and location variables were used as identification variables. The second stage incorporates the inverse Mills ratio (IMR). The IMR (lambda) was not significant implying that increase in the farmer's income is not conditional on the probability of the farmer adopting IPV. This time, only three variables significantly influenced farm income, i.e., acreage under peanut cultivation (PNUTACRES), number of bicycles owned by farmer and the dependency ratio. The size of the peanut farm is positively related to an increase in income from farming. Also, the number of bicycles owned by the farmer, as a private asset, is positively related to higher income from farming. The dependency ratio was surprisingly positively associated with increase in farm income. Perhaps farmers who have high dependency may adopt agricultural technologies that require less labor. For example, during the survey some female respondents hinted that they planted Chinese (IPV) because it was easy to harvest.

Concluding Remarks

The paper examined the factors that determine the adoption of improved peanut varieties and their possible impact on farm income in Northern Ghana. The study reveals that improved peanut varieties are adopted by both male and female farmers. It is worth noting that all female participants cultivated improved varieties. There seem to be no significant differences between adopters and non-adopters, except in number of bicycles owned by the farmer, female farmers and gross farm income. The factors that determine the probability of a farmer adopting an improved variety include membership in a farm organization (i.e., social capital), number of bicycles owned by the farmer (i.e., private asset), early maturity considered important (i.e., characteristic of technology) and Tolon-Kumbungu district (i.e., location). The impact of improved peanut variety adoption on farm income shows that land under peanut cultivation had the most impact on farm income. The rest are number of bicycles owned by the farmer and the dependency ratio.

The study findings emphasize that private assets (number of bicycles), social capital (membership) and location are important to improved peanut variety adoption. Increasing peanut acreage could improve farm income. It is important to note that factors such as education, extension visits and household size do not significantly contribute to either the adoption or income from farming.

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Table 1. The World peanut production (in-shell) in 2010

Rank	Country	Production (MT)
1	China	15,709,039
2	India	5,640,000
3	Nigeria*	2,636,230
4	United States	1,884,950
5	Senegal*	1,286,860
6	Myanmar	1,135,100
7	Indonesia	779,607
8	Sudan*	762,500
9	Argentina	611,040
10	Ghana*	530,887
11	Viet Nam	485,792

Source: FAOSTAT
*African countries

Table 2. Major peanut cultivars grown in the survey area

Variety	Percent of growers
Local (bugla)	11.3
Chinese (Simbaligu)	50.2
Simkarizee	00.5
Mani Pintar (Abain)	38.0

Source: Survey data

Table 3. Variable definitions and their descriptive statistics

Variable	Description	Sample Mean	Standard deviation
Dependent Variable			
Improved Peanut	1 if respondent plants improved varieties, 0 otherwise	0.891	0.312
Independent Variables			
Age	Age of respondent in years	38.456	12.038
Education	1 if respondent has formal education, 0 otherwise	0.15	0.358
Head	1 if respondent is head of household, 0 otherwise	0.45	0.499
Hsize	Number of people residing in household	14.649	8.526
Adult_ Eq	Number of working age members in household (>12 years)	7.776	4.963
Female	1 if respondent is female, 0 otherwise	0.198	0.400
Farm_ org	1 if respondent is a member of a farmer organization, 0 otherwise	0.226	0.419
Credit	1 if respondent has access to credit, 0 otherwise	0.150	0.358
Farmland owned	Number of acres owned by respondent	9.227	9.845
Peanut Area	Number of acres under peanut cultivation by respondent	4.119	3.043
Tractor	1 if respondent owns a tractor, 0 otherwise	0.041	0.98
Extension Contact	Number of times farmer comes in contact with extension agent in a season	1.875	1.107
TV/Radio	1 if respondent owns either a radio or a TV, 0 otherwise	0.796	0.404
bicycle	Number of bicycles owned by respondent	1.29	0.994
Share_f (%)	Female member of the household greater than 12	30.42	11.354
spray	1 if farmer sprays his/her farm with agro-chemicals during the season, 0 otherwise	0.344	0.476
Hire_lab	1 if farmer hires labor during the season, 0 otherwise	0.539	0.4996
soybeans	1 if farmer cultivates soybeans, 0 otherwise	0.243	0.430
Motor cycle	1 if respondent owns a motor cycle, 0 otherwise	0.256	0.437
Bullocks	Number of bullocks owned by farmer	0.077	0.355
OFF_Farm	1 if respondent has off-farm income	0.341	0.475
SND	1 if respondent is located in the Savelugu-Nanton District, 0 otherwise	0.410	0.493
TOL_KUM	1 if respondent is located in the Tolon -Kumbungu District, 0 otherwise	0.590	0.493

Table 4. Differences between farmer adoption and non-adoption status (sample mean)

Variable	Adopters	Non-adopters	Difference	t-value
Gross peanut income (GHC)	413.97	411.46	2.52	0.0237
Gross total farm income	802.82	1,518.75	-715.93	-1.9477*
Males over 12yrs	4.307	4.625	-0.318	-0.4655
Females over 12 yrs	4.615	4.291	0.324	0.4698
Household head	0.441	0.6217	-0.1807	-1.6424
Age	38.68	36.82	1.86	0.6879
Education	0.1538	0.1304	0.0234	0.2949
Female	0.2244	0.00	0.2244	2.6247***
Household size	14.673	14.375	0.298	0.2051
Dependency ratio	0.405	0.435	-0.03	-0.8800
Total farm acreage (#of acres)	9.127	10.145	-1.018	0.4754
Peanut acreage (# of acres)	4.038	4.833	-0.795	-1.2045
Tractor (Dummy)	0.0408	0.0416	-0.008	-0.0186
Extension visits (#)	1.842	2.166	-0.0324	-1.3526
Spray (dummy)	0.3608	0.217	0.1438	1.3709
Credit access (dummy)	0.154	0.125	0.029	0.3721
Off-farm income (dummy)	0.352	0.2608	0.0912	0.8697
Own tv or radio set (dummy)	0.7908	0.833	-0.0422	-0.4819
Own bicycle (#)	1.239	1.666	-0.427	-1.998**
Own motorcycle (dummy)	0.247	0.333	0.086	-0.9073
Farm organization member	0.229	0.208	0.021	0.2307
Number of farmers	196 (89.1%)	24(10.9%)		

*Significant at $\alpha = .1$.
**Significant at $\alpha = .05$.
***Significant at $\alpha = .01$
Source: Survey data

Table 5. Results of the probit model

Variable	Coefficient	Robust Standard error	Z	Marginal effects
Age	0.00326	0.0114	0.29	0.0004
Education	-0.2127	0.3762	-0.57	-0.0293
Hsize	0.0064	0.1383	0.46	0.0008
Membership	0.7788	0.3971	1.96	0.0701**
Credit	0.0835	0.4833	0.17	0.0081
Peanut Area	-0.0710	0.041	-1.68	-0.0087*
Extension Contact	-0.0539	0.1248	-0.43	-0.0066
Bicycles (#)	-0.0318	0.1299	-2.45	0.0389
Share of females (%)	0.0120	0.0131	0.92	0.0014
OFF_Farm	0.2001	0.2985	0.67	0.0233
Dependency ratio	-0.9857	0.7244	-1.36	-0.1209
Maturity time	0.06587	0.2628	2.52	0.1037*
TOL_KUM	-0.6618	0.3029	-2.18	-0.0782**
Constant	1.848	0.7258	2.55	
Log-likelihood	-54.43			
χ^2	7.91			
Probability of χ^2	0.0093			
N	196			

* Significant at α = .1.
** Significant at α = .05.
*** Significant at α = .01.

Table 6. Determinants that influence adoption of IPV and possible Impact on IPV: Heckman two-stage model results

	Probit equation			OLS equation	
Variable name	Estimated coefficient	Z		Estimated coefficient	Z
Age	0.003	0.23		-0.003	-0.68
Education	-0.196	-0.45		0.096	0.47
Hsize	0.006	0.31		-0.011	-1.57
Extension visits	-0.067	-0.53			
Membership	0.8174	1.87*		0.106	0.56
Credit	-0.017	-0.04		0.084	0.43
peanut acreage	-0.073	-1.57		0.183	7.52***
Bicycles	-0.311	-1.95*		0.285	3.45***
Share of females	0.0117	0.92		-0.001	-0.22
Off-farm activities	0.205	0.64		0.0855	0.60
Dependency_ratio	-1.003	-1.05		0.731	1.71*
Early Maturity	0.688	2.40**		-0.046	0.21
Tolon-Kumbungu dist.	-0.634	-1.93*			
Constant	1.844	1.79*		5.190	11.64***
Mills Lambda				-0.4536	-0.63
Rho				-0.541	
Wald Chi-square(13)				100.68	

* Significant at $\alpha = .1$.
** Significant at $\alpha = .05$.
*** Significant at $\alpha = .01$.