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Examining Self-Selection and the Impacts of Integrated Pest Management Adoption on Yield and Gross Margin: Evidence from Ghana

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Abstract

This article investigates the impact of Integrated Pest Management (IPM) adoption on yields and gross margins of vegetable farmers using survey data from the Ashanti Region in Ghana. A parametric approach that accounts for selection bias in IPM adoption is employed to evaluate the direct impact of adoption of pest monitoring only, pesticide application only and both pest monitoring and pesticides application on yields and gross margins. The empirical results from the study show selectivity effects for the impact of adoption of pest monitoring and adoption of both IPM practices on yields of vegetable farmers but no selectivity effects for the impacts on gross margins. Assessment of yield and gross margin of IPM adopters in sub-Saharan Africa must account for selectivity effects.

Keywords: Ghana; Gross Margin; Impact Assessment; Integrated Pest Management; Selection Bias; Yield

JEL codes: C35; J24; Q16; Q18

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1. Introduction

The use of chemical inputs plays a crucial role in agricultural production in many developing countries, including Ghana. Although agro chemical use is effective in controlling pest and reducing yield loss, it has been associated with negative externalities on human health and the environment (Wilson and Tisdell, 2001). According to World Health Organization (WHO) standards, most of the pesticides used by vegetable farmers in Ghana are either banned or very toxic. Mitigating the negative effects of increased pesticides use by smallholder farmers in developing countries has become paramount. To reduce the alarming rate of pesticide use in sub-Saharan Africa, strategies such as outright ban of toxic pesticides (Belder *et al.,* 2006), the imposition of valorem Tax and VAT on pesticide (Agne, 2000, Dinham, 2003) have been implemented by various governments. However, banned pesticides eventually end up in the production systems of most developing countries (Dinham, 2003; Belder *et al*., 2006) making banning of toxic pesticides ineffective policy option in Sub-Saharan Africa.

In terms of environmental sustainability and profitability of agricultural production in developing countries, it is argued that IPM is an appropriate method that could minimize the use of pesticides (Wolff and Recke, 2000; Wilson and Tisdell, 2001; MoFA, 2011). Integrated Pest Management (IPM) strategies are effective for increasing agricultural production without upsetting the balance of nature while controlling pest (Fernandez-Cornejo, 1996). It empowers farmers to promote the health of crops with a well-balanced agro-ecosystem and emphasizes on the use of a combination non-chemical methods and judicious application of chemical inputs in production (Dent, 2000). IPM practices may include the integration of biological, mechanical, cultural and pest management practices based on continuous pest monitoring (Alston and Murray, 2014). Although pesticides application is relevant in controling pest and disease in agriculture, pest monitoring tends to be one of the principal elements in IPM implementation. Effective IPM requires regular field monitoring of pest conditions to the identification of the critical periods for the recommended pesticide application or other control measures.

The growing body of literature on IPM in Africa have largely been limited to analyzing perceptions of pesticide use (Ntow *et al*., 2006), and the nature and determinants of IPM adoption (McNamara *et al*., 1991; Wolff and Recke, 2000; Mugisha *et al*., 2004; Hassan and Bakshi, 2005; Rasouli-Azar *et al*., 2008: Aubert *et al*., 2013). Others studies have focused on the uncertainty of IPM profitability (Abara and Singh, 1993), the benefits accrued from IPM (Dent, 2000), and the health-related and environmental effects of adopting IPM practices (Fernandez-Cornejo and Ferraioli, 1999). Studies that have assessed the impact of IPM adoption have considered the reverse causality of the impact of Farmer Field Schools (FFS) on IPM adoption (Erbaugh *et al*., 2007). Less empirical evidence therefore exist on the direct impact of IPM adoption on crop yields and returns of smallholder farmers in sub-Saharan Africa. Moreover, if the presence of unobserved characteristics are not accounted for, it may confound the estimation of yields and returns to IPM adoption. Notably, whether or not vegetable farmers self-select themselves into IPM adoption has not received much attention in the empirical literature.

The empirical analysis in the current paper employs the parametric multinomial logit model that accounts for selection bias to examine the direct impact of adoption of IPM practices on yields and gross margins among vegetable farmers in the Ashanti region of Ghana. The impacts of IPM adoption, disaggregated by pest monitoring only, pesticides application only, and both pest monitoring and pesticides application on yields and gross margins are investigated. This paper provides an empirical contribution by employing the two-step multinomial logit model suggested by Bourguignon *et al.* (2007). The approach, based on the multinomial logit model, allows us to attribute the selection bias in the estimation of the impact of adoption of IPM on yield or gross margin to the allocation of individuals with better or worst unobserved characteristics in IPM adoption, as well as linking the selection bias of individuals to each of the IPM alternatives. Section 2 lays out a simple model of IPM adoption, including the self-selection bias correction through the multinomial logit approach. Section 3 provides a description of the data used in the analysis. Section 4 discusses the empirical results. Conclusions and policy implications are presented in the final section.

2. Conceptual framework

We assume a linear specification for examining examining the impact of adoption of IPM practices on vegetable yields or gross margins. The yield or gross margin (Q_{ik}) regression can be expressed as

$$Q_{ik} = \phi Z'_{ik} + \alpha J_{ik} + \xi_i \tag{1}$$

where i represents individual, Q_{ik} is yield or gross margins for adopting pest monitoring only $(k = 1)$, pesticide application only $(k = 2)$ and both pest monitoring and pesticide application $(k = 3)$, ξ_i is a normal random disturbance term and J_{ik} is a $[0,1]$ dummy variable for adoption in IPM practice with $J_{ik} = 1$ if the individual adopts the IPM practice, and $J_{ik} = 0$, otherwise. The vector Z_{ik} summarizes individual and household characteristics, including demographic characteristics, human capital, and asset structure. The decision of the individual to adopt IPM practice is based on the individual's self-selection rather than random assignment.

We assumed a dichotomous choice for IPM adoption, where the practice is adopted, if the net benefits from adoption are greater than non-adoption. The difference between the net benefits may be denoted as J^*, such that $J^* > 0$. Although J^* is not observable, it can be expressed as a function of observable elements in the following latent variable model:

$$J_{ik}^* = \alpha X_{ik} + \mu_i,\ J_i = 1\ [J^* > 0]. \tag{2}$$

where J_{ik} is a binary variable that equals 1 if the individual *i* adopts the IPM practice and 0 otherwise, α is a vector of parameters to be estimated, X_{ik} is a vector of household and plot level characteristics and μ_i is an error term assumed to be normally distributed. The probability of adoption of IPM practice can be represented as:

$$\Pr(J_{ik} = 1) = \Pr(J_{ik}^* > 0) = \Pr(\mu_i > -\alpha X_{ik}) = 1 - G(-\alpha X_{ik}) \tag{3}$$

where G is a cumulative distribution function with logistic distribution.

Selection bias occurs if unobservable factors influence both the error terms in the adoption (μ_i) and outcome (ξ_i) equations, such that $corr(\mu, \xi) = \rho$. To correct this selectivity bias, we employ the two-step multinomial logit self-selection bias correction (BFG) approach proposed by Bourguignion *et al.* (2007). The advantages of using the BFG multinomial logit self-selection bias correction approach are that (i) it provides a fairly good correction even when there is the presence of unobservable characteristics by allowing for a more informative comparison of the impact of the probability of adoption in more than two IPM practices (ii) self-selection bias is corrected for the outcome equation, even when the "independence of irrelevant alternatives" (IIA) assumption hypothesis is violated.[1]

The BFG approach proceeds in two-steps. In the first step, a multinomial logit model (MNL) that allows correlations between different IPM alternatives is estimated. The MNL is specified as:

$$P_1(\varepsilon_1 < 0 \mid X) = \frac{\exp(X\alpha_1)}{\sum_k \exp(X\alpha_k)};\ k = 1, 2, 3 \tag{4}$$

[1] See previous self-selection bias correction methods by Heckman (1979), Lee (1983), Dubin and McFadden (1984), Schmertmann (1994).

where $\varepsilon_1 = \max_{k \neq 1}(J_k^* - J_1^*) < 0,\ P_1$ is the probability of adopting IPM alternative 1 , k is a categorical variable describing the adoption of an individual in pest monitoring only $(k = 1)$, pesticide application only $(k = 2)$, both pest monitoring and pesticide application $(k = 3)$ and non-adoption of any of the IPM practices. α_k are the consistent maximum likelihood estimates, X is a set of explanatory variables for the IPM adoption alternatives.

In the second step, the impact of adoption of pest monitoring only, pesticide application only, and both pesticide application and pest monitoring on yields or gross margins is specified as:

$$\ln Q_1 = Z_1\phi_1 - \lambda_1\left[\psi_1^*\Gamma(P_1) + \psi_2^*\Gamma(P_2)\frac{P_2}{(P_2 - 1)} + \psi_3^*\Gamma(P_3)\frac{P_3}{(P_3 - 1)}\right] + \upsilon_k \quad (5)$$

where $\lambda_1\psi_1^*$, $\lambda_1\psi_2^*$ and $\lambda_1\psi_3^*$ are the coefficients of the corrected selection bias terms; $\Gamma(P_1)$, $\Gamma(P_2)$ and $\Gamma(P_3)$ are the predicted probabilities from the multinomial logit model, υ_k is the random error term with mean zero and orthogonal to all the terms on the RHS of (5) and the $\phi_1 s$ are estimated with Ordinary Least Square (OLS).[2]

3. Data description

The data employed in the study comes from a cross-sectional data collected on three hundred urban vegetable farmers in the Kumasi metropolis of Ghana. The urban and periurban areas of Kumasi metropolis contribute significantly to the transformation of food systems in the country. Stratified random sampling was used to capture vegetable farmers who have been introduced to IPM practices. Specifically, the Kumasi metropolis has been stratified into six vegetable producing areas by the Agricultural Extension Agents (AEAs) of the Ministry of Food and Agriculture (MoFA) in the Ashanti region of Ghana. These areas include Gyinyase, Georgia Hotel, Weweso, D-line, Manhyia, and Asokore Mampong. Fifty farmers were selected randomly from each of the six strata to obtain a total sample size of three hundred vegetable farmers for the study. The IPM practices investigated in the study include adoption of pest monitoring only, adoption of pesticide application only, and adoption of both pest monitoring and pesticide application.

Table 1 presents the descriptive statistics of the variables used in the regression analyses. The data collected on the households provided information on individual characteristics, household composition, farm characteristics and other institutional characteristics. Also presented in Table 1 are the statistical differences between adopters of pest monitoring only and non-adopters, pesticide

[2] OLS estimation procedure was used to estimate the outcome equation in the second step because the outcome specification captured only the treated for each IPM alternative. Hence the dependent variable for outcome is continuous and do not contain zero observations.

application only and non-adopters, and adopters of both IPM practices and non-adopters.[3] It is evident that there are significant differences between the mean age of the farmer, contract farming, hired labour, availability of labour and extension contacts for adopters of pest monitoring only and non-adopters. Similar significant differences were observed for adopters of pesticide application only and non-adopters. Apart from education, dependency ratio and farm size, the estimated average differences for all the other variables for adopters of both pesticide application and pest monitoring are statistically significant.

TABLE 1

The mean age of vegetable farmers adopting pest monitoring only and pesticide application only is about 49 years, whilst those adopting both IPM practices is about 51 years. The average number of years of education of adopters of both IPM practices exceed those adopting the individual practices. In terms of labour availability for IPM, the reverse seems to be the case. Adoption of pest monitoring only, pesticides application only, and both pest monitoring and pesticides application were all measured as dummy variables, indicating 1 if the farmer adopted any of these practices as IPM strategy. About 21% of the sampled vegetable farmers adopted pest monitoring only, 56% adopted pesticide application only and 12% adopted both IPM practices. Yield was measured as the total output per hectare (GH¢/ha). The average yield for adopters of pest monitoring only is GH¢ 939.9 (US$ 606.04) per hectare and that of pesticide application only is GH¢ 885.97(US$ 571.26) per hectare.[4] Gross margin analysis was used to determine the costs and returns of vegetable production for adopters and non-adopters of IPM practices. The gross margin is often used where fixed capital appears to be a negligible portion of the farming enterprise, especially in the case of smallholder vegetable production in sub-Saharan Africa. The gross margin of a vegetable farmer was computed as the difference between the total revenue and the variable costs.[5] The average gross margin for adopters of both pest monitoring and pesticide application exceeds those adopting other IPM practice alternatives. The average gross margin of adopters of any the three IPM practice alternatives also exceeds that of non-adopters of the IPM practices.

4. Empirical Results

This section presents and discusses the empirical results from the parametric two-step multinomial logit estimation that correct for self-selection bias.

[3] Non-adopters refer to the sub-group of farmers who have not adopted any of the existing three IPM practices.
[4] Exchange rate: 1US$= GH¢1.5157 in September 2011
[5] It is important to note here that the vegetable farmers did not report any sales costs.

4.1. Multinomial logit estimation results

The first step in the two-step multinomial logit analysis involves an estimation of the probability to adopt IPM alternatives by the vegetable farmers given in equation (4). This step provides estimates of the determinants of IPM adoption as well as bias correction terms for the second step. Given that the coefficients from the multinomial logit presented in Table 2 are difficult to interpret, we provide the marginal effects of the estimates on the adoption of pest monitoring only, pesticide application only, and adoption of both pest monitoring and pesticide application for better interpretation of the results (see Table 3). The base variable in the multinomial logit model is non-adoption of the three IPM alternatives. The estimates show that in each specification, the value of the χ^2 square statistic from the Hausman and McFadden (1984) test does not violate the IIA assumption, as the null hypothesis is not rejected. This indicates that distinguishing between adoption of pest monitoring only, pesticide application only, and adoption of both pest monitoring and pesticide application satisfies the basic assumption in Dubin and McFadden (1984).

TABLE 2

The results in Tables 3 reveal that the probability of vegetable farmers adopting pest monitoring only is significantly related to the positive marginal effects of the number of years of schooling and being a member of farmer-based organization. The finding on education is consistent with other empirical studies on the effect of education on adoption of IPM strategies (Dasgupta *et al*., 2004; Aubert *et al*., 2013). Also pointed out by Beckmann *et al*. (2006), farmers are more likely to adopt IPM strategies if they join farmer-based organizations (FBOs). Unlike adoption of pest monitoring only, membership of farmer-based organization tend to decrease the probability to adopt pesticide application only among the vegetable farmers. The possible reason for this may be that as much as recommended pesticide application rates are crucial, one may not have to belong to an FBO before getting such information compared to pest monitoring which requires more knowledge-based approach and easy information flow environment to even detect during regular pest monitoring of the pest conditions to the identification of critical periods for pesticide application or other control measures.

TABLE 3

It is also clear that the likelihood of vegetable farmers adopting pest monitoring only decreases with household size whilst the reverse is the case for farmers adopting both pest monitoring and pesticide application. These statistical results concur with the labor use hypothesis on adoption of IPM in that, vegetable farmers who adopt pest monitoring only may require less labor compared to adopters of both pest monitoring and pesticide application (Fernandez-Cornejo, 1996; Morse and Buhler, 1997; Pingali and Gerpacio, 1998; Ofuoku *et al*., 2009). The negative marginal effect of hired labour use on the probability to adopt pest monitoring only and the positive marginal effect for the adoption of pesticide application only confirm our earlier preposition on the effect of labor on IPM adoption. The empirical results further show that increasing hired labor and for that matter, labor availabilty on the vegetable farm significantly increases adoption of pesticide application only compared to pest monitoring only.

The results also indicate that as farm size or contract farming increases, the propensity to adopt both pest monitoring and pesticide application by the vegetable farmers tend to increase. The findings support the study by Hammond *et al*. (2006) who found a positive correlation between farm size and adoption of IPM by farmers. The empirical findings also lend credence to the hypothesis on the relationship between contract farming and pest control (Eaton and Shepherd, 2001). As the distance from the vegetable farm to the chemical input shop increases, the vegetable farmers tend to increase the adoption of pesticide application only but decrease the adoption of both pest monitoring and pesticide application. The empirical results also indicate that access to credit tends to increase the adoption of pest monitoring only but decreases the adoption of both IPM alternatives. Other variables of interest are the age of the farmer and extension contact, which tend to decrease the non-adoption of the three IPM alternatives.

4.2. Impact of Adoption of Integrated Pest Management on Yields and Gross Margins

The estimated results on the impacts of adoption of pest monitoring only, pesticide application only, and both pest monitoring and pesticide application on yields and gross margins of the vegetable farmers are presented in Table 4. Self-selection correction terms for non-adoption (mills 1), for pest monitoring only (mills 2), for pesticide application only (mills 3), and for both pest monitoring and pesticide application (mills 4) were generated in the first step multinomial model estimation and included in the three IPM impact specifications in the second step. We find some statistically significant selection bias correction terms after employing the BFG strategy, which confirms why we should use the BFG approach to account for unobserved characteristics of vegetable farmers when estimating the impacts of adoption of IPM strategies.

TABLE 4

The empirical results reveal a negative selectivity correction coefficient for non-adoption (mills 1) in the equation explaining the impact of adoption of pesticide monitoring only. This indicates lower yields for the farmers adopting pest monitoring only than randomly chosen vegetable farmers due to the vegetable farmers with better unobserved characteristics shifting from the adoption of pest monitoring only to non-adoption of the IPM alternatives. Exhibiting downward bias in yields, what the result suggests is that if selectivity bias correction was not taken into account, the yields of the vegetable farmers who adopted pest monitoring only would have been overestimated (Dimova and Gang 2007). The possible reason for this observation is that perhaps the adoption of pest monitoring only led to inefficient allocation of resources and that individuals that would have been better-off adopting pest monitoring only rather shifted to non-adoption of the three IPM strategies. Similar interpretations could hold for the significant negative selectivity bias correction terms for the adoption of both pest monitoring and pesticide application (mills 4) in the impact equation of adoption of pest monitoring only, the selectivity term for non-adoption of the three IPM alternatives (mills 1) in the impact equation of adoption of both pest monitoring and pesticide application, and the selectivity term for the adoption of pest monitoring only (mills 2) in the impact equation of both pest monitoring and pesticide application.

The coefficient of the selectivity bias correction term for the adoption of pesticide application only (mills 3) is positive and significant in the equation explaining the impact of adoption of pest monitoring only. A positive selectivity bias correction coefficient related to pesticide application only in the equation explaining the impact of adoption of pest monitoring only suggests higher yields for farmers who adopt pest monitoring only compared to farmers chosen at random, due to the allocation of farmers with worse unobserved characteristics shifting from adoption of pest monitoring only to pesticide application only. The same interpretation holds for the positive selectivity correction term of the adoption of pesticide application only (mills 3) in the impact eqquation of adoption of both pest monitoring and pesticied application. However, we do not observe the presence of sample selection effects for the impact of the IPM practice alternatives examined in the current paper on gross margins of the vegetable farmers since none of the selectivity correction terms is statistically significant even at the 10% level.

5. Conclusion and Policy Recomendations

This study has investigated the impact of adoption of IPM practices on yields and gross margins of vegetable farmers after accounting for sample selection effects. These impacts were investigated for the adoption of pest monitoring only, adoption of pesticides application only and the adoption of both pest monitoring and pesticide application. The data used are from a survey on farm households in the Ashanti region of Ghana. A parametric BFG multinomial logit model was employed to account for selection bias that normally occurs when unobservable factors influence both adoption of IPM practices and yields or gross margins. The findings from the two-step multinomial logit model show selectivity effects for the impact of adoption of IPM alternative practices on yield of vegetable farmers but no selectivity effects for the impacts on gross margins, thus reiterating the effects of price and market incentives on the overall welfare of smallholder farmers in developing countries.

The findings presented in this study appear to support the growing interest of policy makers in promoting the use of IPM practices in sub-Saharan Africa. Given the absence of organic methods for producing vegetables in most developing countries, policy measures could target vegetable farmers in both urban and peri-urban areas of developing countries to improve their adoption in IPM practices. Improving the human capital base of rural households through easy access to education and informal training programs and facilitating easy access to institutional or informal micro-credit schemes are policy options needed to encourage the adoption of IPM practices with the goal of improving the yields of smallholder farmers and reducing the health-related risks of pesticide use in vegetable production in sub-Saharan Africa.

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Tables and Figures

Table 1: Variable definition and descriptive statistics

Variable	Definition	Pest monitoring only N=64(21%)	Pesticide application only N=168(56%)	Both N=35 (12%)	Non-adopters N=33(11%)
Outcome variables					
Yield	Output per hectare (GHC/ha)	939.92	885.97	857.54	941.70
		(489.39)	(431.58)	(398.23)	(381.98)
Gross margin	The difference between revenue and costs	1723.57***	1380.59***	2174.71***	1095.21
		(745.57)	(832.30)	(711.60)	(464.10)
Independent variables					
Household characteristics					
AGE	Age of farmer in years	48.81**	49.30***	50.37***	43.5
		(8.07)	(9.13)	(7.62)	(9.65)
EDU	Number of years of formal education	6.16	4.85	5.31	5.06
		(5.92)	(5.07)	(6.15)	(5.07)
DPRATIO	Dependency Ratio (>16 and > 65) to the working age (16-65)	0.49	0.45	0.70	0.58
		(0.41)	(0.45)	(0.42)	(0.50)
HHSIZE	Household size	6.44	6.60	7.23*	6.15
		(2.27)	(2.45)	(2.72)	(3.01)
AVAILAB	1 if labor is readily available, 0 otherwise	0.80	0.80***	0.77***	0.39
		(0.41)	(0.40)	(0.43)	(0.50)
Farm characteristics					
FSIZE	Area of land under vegetable cultivation (Ha)	1.31	1.43	1.11	1.35
		(0.81)	(0.99)	(0.76)	(0.97)
CFARM	if farmer is practicing contract farming	0.56***	0.50**	0.66***	0.24
		(0.50)	(0.50)	(0.48)	(0.44)
DISTPEST	Distance from farm to pesticide sales center (Km)	3.09	4.46	2.09***	5.39
		(3.22)	(4.89)	(1.12)	(4.72)
HLAB	1 if farmer employed hired labour, 0 otherwise	0.44*	0.66***	0.54***	0.24
		(0.50)	(0.47)	(0.51)	(0.44)
Institutional characteristics					
FBO	1 if farmer is a member of farmer-based organization, 0 otherwise	0.33	0.13	0.46***	0.18
		(0.47)	(0.33)	(0.51)	(0.39)
ACSCRED	1 if farmer has access to credit, 0 otherwise	0.67	0.60	0.29**	0.58
		(0.47)	(0.49)	(0.46)	(0.50)
EXTVISIT	Number of extension visit in a month	2.91	2.88**	3.51***	1.94
		(1.92)	(1.94)	(1.62)	(1.54)

Note: Asterisks (* and **) indicate statistically significant differences in the respective variables between the two subsamples (i.e., adopters of the IPM practice and non-adopters). The null hypothesis of no difference was tested using a simple *t*-test.
Standard deviations are in parentheses

Table 2: Coefficients of Multinomial Logit Estimates of Adoption of IPM Practices

VARIABLES	Pest Monitoring only	Pesticides Application only	Both Pest Monitoring and Pesticide Application
AGE	0.097**	0.073*	0.051
	(0.043)	(0.041)	(0.051)
EDUC	0.109**	0.056	0.131**
	(0.053)	(0.049)	(0.063)
DPRATIO	-1.027	-0.816	0.490
	(0.705)	(0.653)	(0.804)
HHSIZE	-0.321**	-0.204	0.029
	(0.162)	(0.152)	(0.183)
FSIZE	1.144**	0.881**	1.667***
	(0.451)	(0.412)	(0.590)
CONTFARM	1.717***	1.401**	2.663***
	(0.617)	(0.571)	(0.741)
HLAB	0.736	1.816***	0.869
	(0.611)	(0.557)	(0.715)
AVAILAB	1.759***	1.934***	1.542**
	(0.567)	(0.505)	(0.673)
DISTPEST	-0.314***	-0.188***	-0.695***
	(0.094)	(0.071)	(0.259)
FBO	1.428*	0.050	1.591*
	(0.781)	(0.762)	(0.842)
ACSCRED	0.791	0.316	-1.570**
	(0.615)	(0.556)	(0.730)
EXTVISIT	0.457**	0.463***	0.619***
	(0.189)	(0.178)	(0.202)
Constant	-5.821***	-4.354***	-7.230***
	(1.733)	(1.545)	(2.132)
Log-likelihood		-264.342	
Pseudo R-squared		0.2323	
Chi-square (36)		159.95***	
Observations		300	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Marginal Effects of Adoption of IPM Practices from Multinomial Logit Model

VARIABLES	Pest monitoring only	Pesticides Application only	Both	Non-adoption
AGE	0.005	-0.001	-0.001	-0.003*
	(0.004)	(0.005)	(0.001)	(0.002)
EDUC	0.009*	-0.009	0.003	-0.003
	(0.005)	(0.006)	(0.002)	(0.002)
DPRATIO	-0.057	-0.024	0.051*	0.030
	(0.067)	(0.073)	(0.028)	(0.025)
HHSIZE	-0.025*	0.007	0.010*	0.008
	(0.015)	(0.016)	(0.006)	(0.006)
FSIZE	0.047	-0.041	0.029*	-0.036**
	(0.046)	(0.049)	(0.015)	(0.017)
CONTFARM	0.057	-0.046	0.050**	-0.061**
	(0.057)	(0.064)	(0.026)	(0.026)
HLAB	-0.165***	0.250***	-0.023	-0.062**
	(0.061)	(0.063)	(0.020)	(0.028)
AVAILAB	0.003	0.122	-0.009	-0.116***
	(0.067)	(0.077)	(0.022)	(0.047)
DISTPEST	-0.019	0.029**	-0.019***	0.009***
	(0.012)	(0.013)	(0.006)	(0.003)
FBO	0.257***	-0.296***	0.056	-0.018
	(0.085)	(0.084)	(0.036)	(0.020)
ACSCRED	0.106*	0.004	-0.098**	-0.012
	(0.059)	(0.071)	(0.044)	(0.021)
EXTVISIT	0.002	0.009	0.007	-0.017**
	(0.015)	(0.017)	(0.005)	(0.007)
Observations	300	300	300	300

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Impacts of Adoption of IPM Alternatives on Yield and Gross Margin

	Pest Monitoring Only		Pesticide Application Only		Both Pest Monitoring and Pesticide Application	
VARIABLES	Yield	Gross Margin	Yield	Gross Margin	Yield	Gross Margin
AGE	-1.091**	0.045	-0.167	-0.448	-0.134	-0.560
	(0.412)	(1.039)	(0.184)	(0.317)	(0.101)	(2.234)
EDUC	0.683	0.112	-0.246	0.072	0.134	-3.291
	(0.855)	(1.742)	(0.302)	(0.372)	(0.214)	(4.254)
HHSIZE	4.840**	-1.190	0.671	2.058	0.091	1.040
	(1.819)	(3.721)	(0.851)	(1.466)	(0.572)	(13.055)
DPRATIO	26.403***	-2.904	1.801	9.927	3.918*	-10.421
	(4.654)	(13.720)	(3.945)	(6.822)	(2.006)	(49.892)
FSIZE	0.748	-2.989	-1.924	-0.515	-1.535	-21.627
	(5.222)	(13.012)	(2.483)	(3.121)	(1.193)	(28.653)
CONTFARM	0.242	-6.539	-2.529	-0.973	-5.203***	-33.580
	(7.327)	(20.060)	(3.734)	(4.812)	(1.697)	(43.496)
HLAB	-47.268**	-15.208	2.183	-12.806	-22.166***	53.833
	(18.228)	(50.752)	(5.566)	(10.833)	(5.083)	(96.057)
AVAILAB	-33.320***	-7.384	-1.369	-10.764	-13.766***	10.621
	(7.163)	(30.373)	(3.557)	(7.556)	(1.753)	(36.968)
DISTPEST	-5.259**	0.847	0.689	-1.454	-0.791	12.149
	(2.437)	(5.473)	(1.375)	(1.791)	(0.728)	(16.934)
FBO	31.280	8.569	-5.144	6.866	13.786**	-76.659
	(21.883)	(47.079)	(6.915)	(9.588)	(5.811)	(110.959)
ACSCRED	-25.349***	9.975	-2.102	-10.433	2.296	9.446
	(7.529)	(15.035)	(4.779)	(8.031)	(3.174)	(77.700)
EXTVISIT	-4.392***	-2.451	-0.480	-1.520	-2.930***	-2.660
	(1.532)	(6.422)	(0.690)	(1.342)	(0.297)	(8.131)
mills1	-3.423***	-0.927	-0.247	-1.186	-1.539***	-0.295
	(0.800)	(3.458)	(0.405)	(0.832)	(0.147)	(3.565)
mills2	-2.176	-2.286	0.857	-0.003	-2.550**	8.910
	(3.498)	(7.202)	(0.808)	(1.271)	(0.959)	(18.504)
mills3	7.952**	2.595	-0.616	1.998	3.752***	-12.145
	(3.778)	(9.449)	(1.116)	(1.920)	(1.045)	(19.731)
mills4	-3.271***	0.747	0.025	-1.160	-0.130	3.448
	(0.569)	(1.540)	(0.611)	(0.928)	(0.301)	(7.861)
Constant	3.403	12.494	11.026	6.360	4.552	103.092
	(27.060)	(64.433)	(11.609)	(14.482)	(5.897)	(132.541)
Observations	64	64	168	168	35	35
$F(n, n-k)$	31.89***	1.74*	7.92***	1.59*	20.462***	2.97***
R^2	0.468	0.261	0.284	0.099	0.998	0.352

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1