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HEALTH COST OF PESTICIDE USE ON RICE CULTIVATION IN THE SOUTH-WEST REGION OF BANGLADESH

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ABSTRACT

The study concentrates on assessing health hazards caused by pesticide spray in rice cultivation in the South-west region of Bangladesh. The data particularized that the probability of facing discomfort due to pesticide exposure is 79 percent. The cost-of-illness (Mitigation cost and income loss due to sickness) and avertive action are considered to estimate pesticide use costs. For health cost estimation, a household survey on rice farmers was conducted. The data were collected through an interview method by using a well-structured questionnaire. Logit, Probit, Poission regression, and Negative binomial regression models have been applied in this study. The predicted probability of falling sick from pesticide-related symptoms is significantly higher among individuals who apply pesticides with high chemical concentrations. For both the logit and probit models, it is statistically significant at a 5 percent significance level. On the other hand, an Integrated Pest Management (IPM) application, first aid knowledge, avertive action, treatment facilities, and knowledge level help reduce the probability of diseases caused by pesticide exposure. Finally, the study finds BDT 5273 per person per season as the health cost for pesticide application-oriented health hazard.

KEYWORDS: Pesticide use, Avertive action, Mitigation action, Health Cost.

1. INTRODUCTION

Nowadays, in order to secure high yield, Pesticides are frequently used in the agriculture sector. However, rapid use of it causes contamination of soil, ground, and surface water. It also increases the health risk of farmers. Pimentel (2005) mentioned that every year worldwide uses of pesticides causes 26 million non-fatal poisonings, among which three million affected people are hospitalized, 220 thousand died, and about 750 thousand experiences chronic illnesses. Exercise of pesticide application has significant chronic health effects, including cancer, neurological effects, diabetes, respiratory diseases, fatal diseases, and genetic disorders. These health effects are different depending on the degree and the type of exposure (Choudhary et al., 2014).

Recently for developing countries, the present agricultural systems have "locked in" farmers in the culture of pesticide spray, and it "entrapped" them in pesticides that cause health risk (Atreya et al., 2012). Peasants apply pesticide as an essential input to ensure optimal harvest (Kabir &

Rainis, 2012). Palikhe (2002) has argued that pesticides are generally used to secure yields and improve food quality, but their non-cautious use pollutes the environment and creates a health hazard.

Major health-related issues due to pesticide exposure are skin irritations, eye irritation, vomiting, shortness of breath, headache, fever, stomach poisoning, skin effect, respiratory tract effect, pain in muscles, joint or bone pain, decrease sight, sputum formation, wheezing, blurred vision, burning of the nose, tenderness, decreased chest expansion a rash or cramps and breathing problem (Choudhary et al., 2014; Miah et al., 2014; Bhattacharjee et al., 2013; Atreya, 2005; Dasgupta et al., 2005a; Pimentel, 2005; Khan, 2004; Maumbe & Swinton, 2002; Pingali et al., 1994). Hence, Wilson and Tisdell (2001) claim that proper economic valuation of pesticide-centric risk to human health is essential to trace out for effective policy formulation. Therefore, the paper focuses on the health cost estimation of farmers who use pesticides. To address the objective, the following research questions are considered:

i. What is the impact on farmers' health concerning the dose of pesticide use?

To answer this question, the study investigates the farmer's positive or negative response in the probability of falling sick concerning pesticide use. In this context, authors develop a dose-response model followed by Atreya (2007) and Devi (2007).

ii. What is the amount of monetary loss due to the health cost of pesticide toxicity?

This research question answers the health cost of pesticide exposure. Authors consider medical cost and workday loss as a cost that result from pesticide exposure. The cost of taking avertive action is also included as a cost component.

2. MATERIALS AND METHOD

2.1 Study Area and Sampling Technique

Koyra Upazilla has significant importance in agricultural activities, especially for rice production (Khanom, 2016). Modinabad and Kalna are the two villages considered the study area, and 35 samples were collected from each of the regions (See Table 1). A purposive sampling technique was considered for sample selection. Peasants who spray pesticide were considered the sample for analyzing the impact of pesticide exposure on health costs.

2.2 Data Collection

Primary data were used for the study. Data about the farmer's socio-demographic feature, avertive action-centric activities, mitigation activities, details of sick days related information, smoking habits, working hour, and income were collected by interview schedule method. Data on pesticide exposure and health cost (mitigation cost, avertive cost, and workday loss) were collected using a recall method of last season of paddy harvesting. The pattern of pesticide use is different for different crops. Its consequences are also different. Hence, to ensure group homogeneity of the data, one crop was considered. Here, the study considers paddy crop as it is dominantly cultivated in the study area. Details of the variables are mentioned in Table 2.

2.3 Analytical Framework

Analytical Tool for Research Question 1

The Dose-Response model estimates the health risk associated with pollution. It measures the relationship between the probability of illness and the level of pollution arising from pesticide exposure and other variables that affect the individual's health status (Devi, 2007). In this study, the peasant's probability of falling sick due to pesticide exposure was estimated through dose-response. Since the dependent variable is dichotomous maximum likelihood method is followed for probit model estimation.

On the other hand, avertive action is an essential issue of this study. It concentrated on the farmers' protective activities to protect themselves from discomfort caused by pesticide use. The probability of taking avertive action was considered as a function of the level of pesticide exposure and the vector of explanatory variables. This study follows other scholars' studies (Atreya, 2008; Devi, 2007; Dasgupta et al., 2005b; Dasgupta et al., 2003). The econometric model specification used for dose-response and avertive action function is:

$$S_i = \sum_{i=1}^{n} \beta_i x_i + \mu_i \quad (1)$$

$$Y_i = \sum_{i=1}^{n} \alpha_i z_i + \theta_i \quad (2)$$

In equation 1 and 2, E (μ_i) = 0, E (θ_i) = 0, Var E = σ^2i and Var E (θ_i) = σ^2i; S_i is a binary dependent variable of the probability of falling sick, Yi is the probability of farmers taking avertive action, β_i is the vector coefficient of the probability of falling sick, α_i is the vector coefficient of the probability of taking avertive action, x_i and z_i are the vector of explanatory variables. The vector of explanatory variables comprises individual characteristics, pesticide dose, socioeconomic, and some environmental factors (Atreya, 2008). Here, pesticide dose is defined as concentration (ml or gm/l) multiplied by spray duration (h/day) i.e.

$$D = C_{ni}(t_i) \quad (3)$$

In equation 3, a dose of pesticide (D) is the magnitude of pesticide exposure. C_n(t) is the concentration of exposure as a function of time (t) (Atreya, 2008). The greater the pesticide exposure, the greater is the probability of falling sick and taking avertive action. The data in this regard were collected from a field survey.

Analytical Tool for Research Question 2

This segment of the paper identifies the monetary cost associated with acute symptoms resulted from pesticide exposure. The cost of illness method is used to determine the monetary loss associated with health effects arise from pesticide application following Devi (2007). Therefore, the illness cost comprises doctor consultation fee, hospitalization cost, laboratory test cost, medicine cost, travel cost to the doctor or hospital from home, dietary expenses resulting from illness, and workdays' loss.

Health Cost

To estimate health cost, the authors preferred the Tobit model to identify the factors influencing the mitigation cost arise from pesticide exposure. The equation for the Tobit model is as follows:

$$C_i = \sum_{i=1}^{n} \gamma_i k_i + \epsilon_i \quad (4)$$

In equation 4, C_i is the associated health cost of pesticide exposure, γ_i is the vector of coefficient, and k_i is the vector of the explanatory variable.

Income Loss

The same Tobit model is used to explore the factors that influence the income loss of pesticide spraying. As a result, adverse health effects of pesticide exposure. In equation 5, I_i is the associated income loss of pesticide exposure, L_i is the vector coefficient of income loss, and P_i is the vector of the explanatory variable.

$$I_i = \sum_{i=1}^{n} L_i p_i + d_i \quad (5)$$

Sick Days

This part of the study tries to assess how the average sick days due to chemical pesticides are associated with other factors. The authors considered the Poisson regression (PR) model to estimate sick days S_{it}. It was the count type of data. Chicago and Trivedi (1998) urged that PR is suitable for the dependent variable of the count data type. Here *i* is the number of individual respondents, and t is the duration of illness. Therefore, considering pesticide exposure related sickness S_{it}, the Poisson regression model is:

$$Pr\ (S_{it} = S/\ X_{it}) = f\ (S_{it}/\ \lambda_{it}) = \frac{\lambda_{it}^{Sit}\ exp(-\lambda it)}{S_{it}};\ (S = 0, 1, 2, \dots\dots, 9) \quad (6)$$

$$log\ (\lambda_{it}) = X_{it}\beta_i + \mu_i; \qquad \mu_i \sim N\ (0,\ \sigma_{\mu}^2) \quad (7)$$

In equation 6 and 7, λ_{it} depicts the mean value of the number of sick days, β_i implies the vector of regression coefficients, and X'_{it} is the vector of explanatory variables. The Poisson distribution is developed on a very restrictive assumption, i.e., equality of mean and variance of the dependent variable. If this assumption is violated, then the alternative approach is to go for Negative Binomial Regression (NBR) (Power & Xie, 1999). Hence, modification of the PR model in NBR as:

$$Pr\ (S_{it} = S/\ X_{it}) = f\ (S_{it}/\alpha,\ \lambda_{it}) = \frac{r\ (S_{it}+\alpha)}{S_{it}!r(\alpha)}\ (\frac{\alpha}{\alpha+\lambda_{it}})\ \alpha\ (\frac{\lambda_{it}}{\alpha+\lambda_{it}})^{S_{it}} \quad (8)$$

$$log\ (\lambda_{it}) = X'_{it}\beta_i + \mu_i; \qquad \mu_i \sim N\ (0,\ \sigma_{\mu}^2) \quad (9)$$

Here α implies dispersion parameter, which quantifies overdispersion. The mean of the dependent variable in NBR is still depicted by E $(S_{it}\ /X_{it}) = \lambda_{it}$. However, the variance is represented as V $(S_{it}\ /X_{it}) = \lambda_{it}/\alpha$. Therefore, the study can move to NBR when α approach infinity.

Health Cost Estimation

Cost of illness (COI) is the most commonly and popularly used method for estimating health cost due to health damage arises from any exposure (Devi, 2007). For this paper, the cost of illness comprises the consultation fee, hospitalization cost, laboratory test cost, medicine cost, travel cost to the doctor or hospital from home, dietary expenses resulting from illness, loss of earnings due to loss of working days or loss of productivity. To estimate the monetary loss of pesticide exposure, this study followed the cost of illness approach used by Atreya (2007). The total predicted health cost (THC) of pesticide exposure is as follows:

$$THC= S^* (AMC+AIL) + Y^* AAC \text{ for pesticide users} \quad (10)$$

We can estimate (predicated probability of illness due to pesticide exposure of pesticide users) and Y (predicated probability of avertive action) from equations 1 and 2. Apart from this, AMC is the average mitigation costs, AIL is the average loss of income due to pesticide exposure, and AAC is the average cost of avertive action. Average Avertive Cost (AAC) reflects the cost of preventive action taken to direct exposure to the pesticide, such as masks, boots, pants, sprayers, etc. Avertive equipment may also have multiple uses. However, this study considered avertive equipment purchased specifically to handle pesticides following Atreya (2007).

3. RESULTS AND DISCUSSION

3.1 Descriptive Analysis

Table 3 depicts descriptive statistics of the variables used in different models in the study. 79% of respondents experienced discomfort after pesticide spray. The average level of education is 7.91 years, with a standard deviation of 2.76. The minimum working hour per day is 6 hours, and the maximum value is 8 hours, with average working hours 6.87 and a standard deviation of 0.51. A mean workday per week is 6.74, with a standard deviation of 0.47.

The minimum medical cost for the last season is BDT 0, and the maximum medical cost is BDT 6175, with an average medical cost of 2215.96 and a standard deviation of 1850.97. Average sick days were 3.04, with a standard deviation of 2.78 in the last season due to pesticide exposure. The maximum value of the sick day is nine, and the minimum value is 0. Here, 0 sick days implies that sprayers did not experience any health hazard after pesticide spray.

3.2 Prevalence of Pesticide Related Diseases

Table 4 depicts the probability of pesticide sprayer peasants' facing several sicknesses due to pesticide exposure. Headache, eye irritation, weakness, and vomiting are the most common phenomenon of pesticide exposure.

3.3 Probability of Falling Sick

A dose-response function is used to calculate the probability of falling sick. Table 5 postulates the result of dose-response function estimation. Here, the numerical value 1 indicates respondents suffered from any sorts of discomfort due to pesticide application for the last cultivating season and 0 for those who are not suffering from pesticide-related adverse health effects.

Here, one unit increase in the amount of pesticide concentration increased the probability of feeling discomfort by 1.098 percent in the logit model and 1.384 percent in the probit model. An increase in age by one year reduces the probability of feeling discomfort due to pesticide exposure by 3.673 percent and 5.006 percent, respectively. However, subjects' exposure to pesticide spray for a more extended time horizon induces a higher probability of falling sick by

0.044 percent in the logit model and 0.060 percent in the probit model. Therefore, a U-shaped association prevails between age and the likelihood of falling sick. Young people are less vulnerable to pesticide exposure, but age square claims that older adults are at higher risk of facing discomfort. The use of IPM in green pesticides rather than chemical pesticides helps farmers reduce pesticide-related diseases by 14.39 percent and 16.56 percent, respectively. Besides, availabilities of treatment facilities help to reduce the adverse health effect of pesticide exposure. Moreover, the increase in workdays per week and pesticide preparation time boosts the probability of facing discomfort due to pesticide application in the logit and probit model.

3.4 Avertive Action for Different Body Parts

Data in Table 6 shows the pesticide sprayers' probability of taking avertive action. The data reveals that maximum pesticide sprayers have a higher probability of taking avartive action for body cover (0.61), face care (0.7) and leg care (0.7) for different body parts. Hence, the pesticide sprayers' total probability of taking avertive action was 0.7

3.5 Avertive Behavior and Cost Specification

Table 7 shows sector-wise avertive behavior and cost specification of the pesticide sprayers. Among 70 respondents, only 49 respondents adopt avertive action. Here, for foot protection corresponding protective option were boots and shoes. The average cost for foot care and head cover are BDT 518.46 and BDT 137.71, respectively. For eye care, only 24 respondents use sunglasses, and the average cost is BDT 140.21. On the other hand, among 49 farmers, 39 farmers use gloves, and the average cost for gloves is BDT114.74 per person. The 49 respondents used the mask for the face's safety, and the corresponding average cost for masks is BDT 73.93. Furthermore, 31 respondents use full-length trousers for leg protection, and their average protection cost is BDT 510.81.

3.6 Probability of Taking Avertive Action

Table 8 revealed that both in the logit and probit model, pesticide sprayers, who took avertive action experience a lower probability of facing discomfort due to pesticide exposure compared to those who did not adopt avertive action. The value is 1 for those who take protective action when spraying chemical pesticide and 0 who do not use protective equipment.

3.7 Estimation of Loss of Income

In this part, the authors explore a Tobit model to identify factors that influence income loss due to pesticide application. Table 9 depicts that holding other explanatory variables constant increase of age by one year reduces average income loss by BDT517.281 per season. Keeping the other variable remaining same if the square value of age increases by 1 unit, expected income loss due to pesticide exposure increases by BDT7.28 per season. At an earlier age, farmers had better health status and the ability to avoid adverse health effects of pesticide exposure, but farmers suffered an adverse health effect after an individual age.

Considering other explanatory variables, constant respondents with first aid knowledge can reduce income loss per season by BDT 2899.63 compared to those who do not have first aid knowledge. Keeping other variable constant, an increase in pesticide preparing time by 1 minute raise the average income loss per season by BDT 308.88, and this result is significant at 10 percent significance level. Holding other variables remaining the same increase per week workday by one day increases average income loss per season by BDT 1445.48.

3.8 Estimation of Mitigation Cost

Table 10 depicts parameter estimation of mitigation expenditure. Holding other variables constant increase in age by one year reduces the expected mitigation expenditure per season by BDT 512.70, and the result is significant at a 5 percent significance level.

Holding other variable constant farmers with first aid knowledge expected to decrease mitigation cost per season by BDT 2613.478. An increase in weekly working day by one day increases mitigation expenditure due to pesticide-related diseases by BDT 1498.953, keeping other variables constant, and this result is statistically significant at a 1 percent significance level.

3.9 Sick Days Estimation Due to Pesticide Exposure

Poisson regression and negative binomial regression analysis were conducted to explore significant factors that influence respondents' sick days due to pesticide exposure. Here, the dependent variable is the number of sick days. One of the restrictive assumptions of the Poisson regression model is the equality of mean and variance. However, the mean and variance of sick days are not the same for the study. In this context, the authors conducted an over dispersion test, considering the value of alpha (α) in table 11.

Null Hypothesis, $H0 = \alpha = 0$

There was no overdispersion in the data.

Alternative Hypothesis, $H1= \alpha \neq 0$

There was over dispersion in the data.

Here, the corresponding test statistics for Z value was 2.10 where $Z = \alpha / SE (\alpha)$

So, the negative binomial model is justified in this analysis.

Pesticide concentration significantly increases expected sick days due to pesticide exposure (Table 11). Holding other variables constant, IPM users face lower sick days due to pesticide exposure by 0.5145 times in the poission model and 0.5144787 times in the negative binomial model compared to the non-IPM user, and the result is significant at 1 percent significance level. Taking avertive action reduces pesticide application-related sick days due to chemical exposure by 0.40076 times and 0.4006795 times, respectively, which is significant at a 1 percent significance level, holding other explanatory variables constant. Keeping other variables remaining the same increase in pesticide concentration levels raised expected sick days by 1.0556 and 1.055633 times in the poission and negative binomial regression model. Both of the results are significant at a 1 percent significance level.

4. CONCLUSION

The study reveals considerable health costs experienced by the pesticide sprayer. Following the health cost estimation method by Atreya (2008), this study identifies average mitigation cost, income loss due to workdays loss, and avertive cost as BDT2906.31, BDT 2272.77, and BDT 1717.96, respectively (Table 12). Hence, the total cost of pesticide use is BDT 5273.33. The result also manifested that increase in the concentration of pesticides increases the probability of falling sick. Therefore, the sprayer should be careful regarding the mixture of pesticides and their application.

Meanwhile, IPM techniques are found as a beneficial way out to curve pest oriented problem. The data postulated that adoption of IPM techniques reduces the potentiality of pesticide sprayers' health hazard by 51 percent. However, the literature suggests the application of IPM needs training, which makes farmers reluctant to apply it. Only 27 percent of the respondent in the study area used the IPM technique. The result was consistent with Atreya et al. (2012), where he stated that "IPM training leads to higher investment for farmers." Therefore, the government should increase training facilities for the peasants at a cheaper rate so that they will be encouraged to adopt IPM techniques of pest control.

Meanwhile, this paper is an exercise to explore the health risk related to pesticide spraying for one cultivation season. Other researchers can explore a wide range of massive national-level studies on annual health costs due to pesticide exposure in total agricultural production due to pesticide use. This future research option can provide a composite scenario about health hazards from pesticide exposure and its associated health cost.

List of Tables and Figures

Table 1: Sampling Design

Name of the Village	Number of Samples
Modinabad	35
Kalna	35

Source: Authors' Compilation

Table 2: List of Variables

Variables	Description	Literature
Probability of Falling Sick	Dichotomous 0= Not Sick 1= Sick	Devi (2007) and Atreya (2007)
Probability of Taking Avertive Action	Dichotomous 0= Not Sick 1= Sick	Atreya (2007)
Money Spend to Cure Diseases	BDT Per Person Per Season	Authors' Compilation
Loss of Income	BDT Per Person Per Season	Authors' Compilation
Sick Days	Day Per Person Per Season	Authors' Compilation
Dose of Pesticide	Pesticide (ml or gm/l)* (h/day)	Devi (2007)
Mixing of Pesticide	Dummy 1= Mixed 0= Otherwise	Devi (2007)
Age	Years	Devi (2007) and Atreya (2007)
Age2 of Individual	Years	Authors' Compilation
Education	Years of Schooling	Devi (2007) and Atreya (2007)

Variables	Description	Literature
Integrated Pest Management	Dummy 1= Applicator of IPM 0= Otherwise	Devi (2007)
Body Mass Index	Weight/Height2	Devi (2007)
Cultivable Land Area	Bigha	Authors' Compilation
Full Time or Part Time Sprayer	Dummy 1= Full Time 0= Part-Time	Authors' Compilation
Availability of Treatment Facilities	Dummy 1= Yes 0= Otherwise	Authors' Compilation
Work Day Per Week	Day	Authors' Compilation
Pesticide Preparing Time	Minute	Authors' Compilation
Smoking Habit	Dummy 1= Smoker 0= Non-Smoker	Devi (2007) and Atreya (2007)
First Aid Knowledge	Dummy 1= Yes 0= Otherwise	Maumbe and Swinton (2002)

Source: Authors' Compilation.

Table 3: Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
Discomfort	0.79	0.41	0	1
Mixing of Pesticide	0.6	0.49	0	1
Age	40.1	7.91	26	56
Age2	1671.37	658.91	676	3205
Education	7.91	2.76	3	14
IPM Use	0.27	0.45	0	1
BMI	24.34	1.56	20.78	30.27
Smoking Habit	0.33	0.47	0	1
Cultivable Land	18.34	7.85	0	30
Pesticide Sprayer	0.99	0.12	0	1
Treatment Facilities	0.51	0.50	0	1
Avertive Action	0.49	0.50	0	1
Work Hours per Day	6.87	0.51	6	8
Work Days Per Week	6.74	0.47	5	7

Variable	Mean	Std. Dev.	Min	Max
Preparing Time of Pesticide	6.07	1.16	3	8
Medical Cost	2215.96	1850.97	0	6175
Sick Days	3.04	2.78	0	9
Income	18539.29	5182.04	7000	27000
Expenditure	17328.57	4899.63	4500	25000
Savings	5818.57	10977.09	0	50000
Avertive Cost	1717.96	838.68	0	2120
Income Loss	2272.77	1637.67	0	6667

Source: Authors' Compilation.

Table 4: Probability of Attack by Pesticide Related Diseases

Variable Name	Explanation	Value
Eye Irritation	48/70	0.686
Headache	51/70	0.729
Breath Problem	35/70	0.5
Vomiting	46/70	0.657
Skin Irritation	38/70	0.542
Fever	47/70	0.671
Pain	45/70	0.643
Decrease Sight	11/70	0.157
Cough	46/70	0.657
Weakness	51/70	0.729
Here 48, 51, 35, 46, 38, 47, 45, 11, 46, and 51 are frequency of pesticide-related sickness		
55= Total Frequency of farmer face discomfort due to pesticide-related sickness		
15= Total Frequency of farmer do not face discomfort due to pesticide-related sickness		
70= Total number of observation surveyed		
55/70 = 0.786 is the total probability of facing discomfort due to pesticide exposure in the study area		

Source: Authors' Compilation.

Table 5: Result of Dose-Response Function Analysis

Dependent Variable: Probability of Facing Discomfort				
	Logit Model		Probit Model	
Explanatory Variable	Coef.	Marginal Effect	Coef.	Marginal Effect
Concentration	0.31**	0.0109835	0.16**	0.0138457
Mixing	0.92	0.0368209	0.51	0.0497237

Dependent Variable: Probability of Facing Discomfort				
	Logit Model		Probit Model	
Explanatory Variable	Coef.	Marginal Effect	Coef.	Marginal Effect
Age	-1.0*	-0.0367349	-0.57*	-.0500654
Age2	0.01*	0.0004443	0.01*	0.0006002
Education	0.07	0.0025146	0.03	0.0030133
IPM	-2.23	-0.1439332	-1.16*	-0.1655547
BMI	0.65*	0.0224949	0.33*	0.0286576
Cultivable Land	-0.06	-.0034253	-0.06	-0.0050214
Pesticide Sprayer	0.18	0.0067966	0.11	0.0104678
Treatment Facilities	-1.78*	-0.068683	-0.95*	-0.087621
Work Days Per Week	1.80*	0.0647701	0.99*	0.08633
Preparing Time of Pesticide	1.29**	0.0464236	0.68***	0.0592791
Constant	-21.26		-9.24	

Source: Authors' Compilation; N.B.: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 6: Probability of Taking Avertive Action

Variable Name	Explanation	Value
Feet care	39/70	0.557
Headcover	35/70	0.5
Eyecare	24/70	0.343
Body cover	43/70	0.614
Hand care	39/70	0.557
Face care	49/70	0.7
Leg care	49/70	0.7
Here 39, 35, 24, 43, 39, 49, and 49 are frequency of taking avertive action		
49= Total Frequency of farmer take avertive action		
21= Total Frequency of farmer does not take avertive action		
70= Total number of observation surveyed		
49/70 = 0.7 is the total probability of taking avertive action		
Average Avertive Cost = BDT 1717.96		

Source: Authors' Compilation

Table 7: Sector Wise Avertive Cost

Type of Avertive behavior		No. of Respondent Use	Average Cost (BDT)
Feet care	Boots	39	518.46
	Shoes	0	
	Others	0	

Type of Avertive behavior		No. of Respondent Use	Average Cost (BDT)
Headcover	Hat	35	137.71
	Helmet	0	
	Others	0	
Eyecare	Glasses	24	140.21
	Others	0	
Body cover	Full sleeved shirt	34	543.38
	Half sleeved shirt	9	392.22
	Others	0	
Hand care	Gloves	39	114.74
	Others	0	
Face care	Mask	49	73.93
	Others	0	
Leg care	Full-length trousers	31	510.81
	Hard jeans	18	556.94
	Others	0	

Source: Authors' Compilation.

Table 8: Result of Avertive Action Analysis in Logit and Probit Model

Dependent Variable: Probability of Taking Avertive Action				
	Logit Model		Probit Model	
Explanatory Variable	Coef.	Marginal Effect	Coef.	Marginal Effect
Concentration	-0.64***	-0.1578811	-0.36***	-0.143911
Mixing	3.46*	0.6712321	2.07*	0.6775878
Age	0.39	0.0954008	0.262	0.1027862
Age2	-0.01	-0.0012117	-0.01	-0.0013186
Education	-0.51*	-0.1272048	-0.29*	-0.1134545
IPM	3.37*	0.6600703	1.93*	0.6358564
BMI	0.33	0.0820678	0.20	0.0793387
Cultivable Land	0.047	0.0103053	0.03	0.0107543
Pesticide Sprayer	5.15***	0.5656332	2.91***	0.5764699
Treatment Facilities	4.10***	0.766162	2.35***	0.7566728
Work Days Per Week	-0.15	-0.0368014	-0.13	-0.0529039
Preparing Time of Pesticide	-0.39	-0.0958673	-0.29	-0.1145703
Constant	0.81		-9.24	

Source: Authors' Compilation. N.B.: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 9: Tobit Model for Income Loss

Dependent Variable: Income Loss Per Season				
Explanatory Variable	Coef.	Std. Err.	t	P>t
Age	-517.281**	239.94	-2.16	0.03
Age2	7.276***	2.89	2.51	0.01
Education	158.425	100.46	1.58	0.12
IPM	438.721	516.09	0.85	0.39
BMI	56.877	132.92	0.43	0.67
Smoking Habit	-246.259	400.87	-0.61	0.54
Avertive Action	379.663	1462.89	0.26	0.79
Sick Days Per Season	38.749	146.59	0.26	0.79
Concentration of Pesticide	-0.362	54.83	-0.01	0.99
First Aid Knowledge	-2899.63**	1280.42	-2.26	0.02
Pesticide Preparing Time	308.881*	189.20	1.63	0.10
Work Days Per Week	1445.479***	424.19	3.41	0.01
Constant	-2492.27	6944.81	-0.36	0.721
Sigma	1435.895	148.53		
LR chi2	44.79			
Prob > chi2	0.00			
Pseudo R2	0.046			
Log-likelihood	-466.54			
Number of Observation	70			

Source: Authors' Compilation; N.B.: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 10: Tobit Model for Mitigation Cost

Dependent Variable: Mitigation Cost				
Explanatory Variable	Coef.	Std. Err.	t	P>t
Age	-512.700**	254.19	-2.02	0.04
Age2	7.094**	3.06	2.32	0.02
IPM	718.452	506.11	1.42	0.16
BMI	56.691	141.38	0.40	0.69
Smoking Habit	-195.230	428.63	-0.46	0.65
Avertive Action	-488.422	1354.93	-0.36	0.72
Concentration of Pesticide	-78.181	53.46	-1.46	0.14
First Aid Knowledge	-2613.478**	1308.61	-2.00	0.05
Work Day Per Week	1498.953***	445.84	3.36	0.01

Dependent Variable: Mitigation Cost				
Explanatory Variable	Coef.	Std. Err.	t	P>t
Preparing Time of Pesticide	200.541	197.23	1.02	0.31
Constant	1631.72	7071.47	0.23	0.818
Sigma	1570.01	162.31		
LR chi2	43.12			
Prob > chi2	0.00			
Pseudo R2	0.04			
Log-likelihood	-481.39			
Number of Observation	70			

Source: Authors' Compilation; N.B.: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 11: Estimation of Sick Day in Poisson and Negative Binomial Regression Method

Dependent Variable: Frequency of Sick Days				
Explanatory Variable	Poission Regression		Negative Binomial Regression	
	Coef.	IRR	Coef.	IRR
Age	-0.029 (0.101)	0.9712	-0.0293 (0.1007)	0.9711722
Age2	0.0003 (0.001)	1.0004	0.0004 (0.0013)	1.000393
Education	-0.027 (0.039)	0.9733	-0.0270 (0.0395)	0.9733149
IPM	-0.665*** (0.277)	0.5145	-0.6646* (0.2771)	0.5144787
BMI	-0.0115 (0.049)	0.9885	-0.0115 (0.0494)	0.9885193
Smoking Habit	0.103 (0.140)	1.1089	0.1033 (0.1399)	1.108852
Cultivable Land	0.0034 (0.009)	1.0034	0.0034 (0.0086)	1.003407
Work Hours Per Day	-0.050 (0.249)	0.9511	-0.0502 (0.2492)	0.9510857
Avertive Action	-0.915*** (0.341)	0.40076	-0.9146*** (0.3409)	0.4006795
Concentration	0.054*** 0(.020)	1.0556	0.0541*** (0.0201)	1.055633
Preparing Time	0.027 (0.0670)	1.0277	0.0273 (0.06691)	1.0277

Dependent Variable: Frequency of Sick Days				
Explanatory Variable	Poission Regression		Negative Binomial Regression	
	Coef.	IRR	Coef.	IRR
First Aid Knowledge	0.221 (0.219)	1.2470	0.2207 (0.2190)	1.246997
Constant	1.533	4.6305	1.532658 (2.889321)	4.630468
Lnalpha	-16.41 (0.47)	-16.45	-17.27583 (.2175171)	-17.27583
Alpha	0.0000000749 (0.0000000356)	0.0000000749	0.0000000314 (0.00000000683)	0.0000000314
LR chi2		-		-
Prob > chi2		0.00		0.00
Wald chi2		134.52		138.67
Log pseudo-likelihood		-117.53044		-117.26012

Source: Authors' Compilation;
N.B.: Robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 12: Estimation of Health Cost

Probability of a user being sick (S)	0.786
Probability of taking avertive action (Y)	0.7
Average mitigation cost (AMC)	BDT 2906.31
Average Income Loss (AIC)	BDT 2272.77
Average Avertive Cost (AAC)	BDT 1717.96
Average health cost due to pesticide exposure	
THC= S* (AMC+AIC) + Y* AAC	BDT 5273.33

Source: Authors' Compilation

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