Factors that affect the use of herbicides in Philippine rice farming systems

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Abstract

This study involves the application of a random-effects double-hurdle model to survey data to identify the farm-level factors affecting the adoption and intensity of herbicide use in rice production in the Philippines. Results broadly indicate apparent differences in the degree to which important explanatory variables affect the intensity and adoption decisions. The age of the farmer, household size, and irrigation are the significant predictors influencing the decision of farmers to use herbicides, while economic variables such as the price of herbicides, total income of farmers, and the use of bank loans or credit are the highly significant factors determining the intensity of herbicide use. Significant determinants of both the adoption and intensity decisions are land ownership, farm area, and the method of crop establishment used. Results suggest that all of the identified significant predictors in both herbicide use decisions can be considered by the national government when designing policies to reduce excessive use of herbicides or to encourage the adoption of alternative methods of weed control. This is important because for small rice producers, like the majority of Filipino farmers, improved weed management techniques that build on their traditional practices and that are compatible with their resources will be more easily adopted by farmers, relative to those that require radical change to the entire farming system.

Key words. Herbicide use; Double-hurdle model; Adoption; Rice farming system.

1. Introduction

In the Philippines, rice is the staple food of over 80% of its national population and accounts for an important share of total economic activity. The global importance of rice highlights the need to promote efficient production, as demand is expected to double over the next 40 years. The effective management of weeds is one way to achieve this goal. Accordingly, the use of herbicides to reduce weed competition in rice crops is rapidly increasing worldwide. The annual growth rate of herbicide sales for rice crops globally is estimated to be around 60 million (M) US dollars (US$) year^{-1}, exceeding those reported for insecticides (US$47 M) and fungicides (US$41 M) (Zhang et al., 2004). With this estimated growth rate, the global sale of herbicides for application in rice farming systems could reach around US$3 billion year^{-1} by 2025.

In the Philippines, many farmers rely on herbicides to control weeds in their rice fields, particularly for direct-seeded (as opposed to transplanted) crops, as broadcast seed does not grow in consistent rows, making manual weeding less efficient. Manual weeding and flooding are traditionally used to restrict weed competition with crops, but their cost is rising due to increased labor and water resource costs. Herbicides are easy to use, can achieve high rates of control with effective application, and are, in many situations, relatively cheap, compared to manual or mechanical weeding. Indeed, Pingali et al. (1997) estimated that the benefit-cost ratio of applying herbicides in rice farming is almost four times higher than manual weeding. However, the use of herbicides has been accompanied globally by the potential build up of herbicide-resistant weeds, weed species population shifts, and concerns about environmental contamination and impacts on human health (Johnson and Mortimer, 2005).

Rice farmers have generally been encouraged by the Philippine Rice Research Institute (PhilRice) to use integrated weed management (IWM) strategies. This encouragement is primarily aimed at maintaining crop yields, while reducing chemical use. IWM involves the use of a diversity of weed control methods, including non-chemical strategies (such as full cultivation prior to establishment). IWM can benefit the control of rice weeds by delaying the development of resistance and/or allowing the control of herbicide-resistant weeds. The adoption of weed management strategies that increase production and profit without depreciating future productive capacity, such as through resistance development, will be higher where practices build on traditional methods and are compatible with existing practices (Pannell et al., 2006). This is particularly important given the significance of rice to the Philippines and the increasing scarcity of key resources required for traditional farming systems, such as labor and water. A statistical analysis that identifies the impact of various economic and non-economic factors on the adoption and intensity of use of weed management strategies can thus provide valuable input into the formulation of policies to promote sustainable agricultural production.

The objective of this study is to determine farm-level factors driving herbicide demand in rice farming systems of the Philippines. This involves the identification of those factors influencing the adoption and intensity of herbicide use in rice fields. A random-effects double-hurdle model is applied to survey data that collates responses from thousands of producers throughout the Philippines.

The paper is structured as follows. Section 2 describes the method of statistical estimation. Section 3 describes the data set and variables of the model. The results of the analysis are presented and discussed in Section 4. Section 5 concludes.

2. Statistical method of estimation

The double-hurdle statistical model, originally formulated by Cragg (1971) in the context of household demand for products, is applied in this study. This method has many benefits in the context of this study. First, the sets of factors that affect the adoption and intensity of input use can be dissimilar (Wooldridge, 2002). Second, this procedure allows the definition of different types of dependent variables for the adoption and intensity decisions. This is important since the herbicide adoption decision will often be described by a binary variable or censored variable (one that has a lower limit, an upper limit, or both (Greene, 2003)), while the intensity decision is better described using continuous values. Last, in contrast to a Tobit model (Tobin, 1958; Llewellyn et al., 2007), a double-hurdle model is able to represent the fact that failure to adopt can occur due to both economic and non-economic reasons, not just economic factors (Sinning, 2009). For example, producers may not purchase herbicides since they prefer not to work with chemicals, not just because the price is too high or their income is too low.

A double-hurdle model enables the modelling of two separate stochastic processes, each of which may potentially possess their own explanatory variables and parameters (Brouhle and Khanna, 2005). These processes involve (1) the decision to use an input (first hurdle), and (2) the intensity of use (second hurdle) (Wooldridge, 2002). The model is based on an assumption that these two separate hurdles or stages must occur before a positive level of input use is observed. Both hurdles are estimated separately in this study, based on an assumption that there is no correlation between the error terms of the two hurdles, implying that the two decisions are made independently of each other. A Probit model is used to study the determinants of adoption and a Tobit model is used to determine what drives the intensity of input use (Blundell and Meghir, 1987). These models are preferred to ordinary least squares (OLS) regression since OLS will result in biased and inconsistent parameter estimates, as the dependent variable for the adoption equation is discrete, while the dependent variable for the intensity of use equation is censored from its lower limit (the case of zero observations) (Wooldridge, 2002).

The model is applied here to "panel data": a cross-sectional sample of respondents providing data in several time periods. A random-effects model (REM) (Wooldridge, 2002) is used. It is based on the assumption that the intercept of an individual unit is randomly drawn from a distribution that exists for a larger population and is expressed as a deviation from the population's constant mean value. It is also assumed in a REM that the intercept is uncorrelated with the independent variables. REM has multiple benefits over a fixed-effects estimator (Wooldridge, 2002). First, it provides more degrees of freedom since there is no need to estimate individual specific intercepts (Maddala, 1987). Second, REM takes into account not only the effects of observable variables on the dependent variable, but also the effects of unobserved heterogeneity among the individuals. Indeed, most applications involving panel-data models make use of the random-effects estimator, as it captures the unobservable individual specific effects of the variables (Baltagi, 1995). Last, the random-effects estimator is superior where there are some time-invariant observations. This is appropriate here, as some variables used in the estimation (e.g. education and farm location) do not vary with time in the data set.

A panel double-hurdle model has been applied previously in a number of studies applied to the study of agricultural inputs (e.g. Dong et al., 2001; Abera, 2008). However, this application adds to this literature in that it analyses the determinants of herbicide demand in Philippine rice crops, which requires various modifications of the standard procedure that are now outlined.

The first stage of the panel double-hurdle model is the estimation of adoption of herbicide. Unlike the Dong et al. (2001) estimation, farmers in the sample are treated individually based on their classification (user or non-user of herbicide). This approach is more appropriate than using a panel of N farmers because using all observations would only lead to an inefficient estimate of adoption, as different predicted probabilities will be obtained for the same farmer over T time periods. Given the nature of the data, a cross-section Probit regression is used in this study. The information that is used in the estimation is taken only in the year that an individual farmer is first interviewed. The equation representing the adoption decision of an individual farmer is represented as:

$$D_i = \begin{cases} 1, & \text{if} \quad u_i > -w_i\alpha \\ 0, & \text{otherwise} \end{cases} \qquad i = 1,\ldots,N, \tag{1}$$

where D_i is a binary dependent variable which is equal to 0 if the i^{th} farmer is not a user of herbicides for all survey periods and equal to 1 if the i^{th} farmer used herbicide for at least one time period. In addition, w_i are the explanatory variables where some of these also exist as explanatory variables in the regression identifying the determinants of the level of herbicide use. The regressors include both economics and non-economic factors, with a leaning towards the latter because it is assumed that economic factors mainly come into play once farmers decide to use herbicides (Newman et al., 2003). The α are the estimated coefficients and u_i is an error term that is assumed to be distributed normally with mean zero and constant variance σ^2. Given the observed binary decision (D_i), the regression equation of the unobserved "latent" variable (D_i^*) is described as:

$$D_i^* = w_i\alpha + u_i, \tag{2}$$

In the second stage of the model, consider a panel of N farmers whose herbicide use is observed over T time periods. This yields a data array for the i^{th} farmer, y_i and x_i where y_i is a $T \times 1$ vector of the observed amount of herbicide use and x_i is a $T \times K$ matrix of explanatory variables. To determine the level of herbicide use over time, a random-effects Tobit model is applied in this study. The censoring rule of the Tobit model is described as:

$$\begin{aligned} y_{it} &= y_{it}^*, \quad \text{if} \quad e_{it} > -x_{it}\beta_1 - \lambda_{it}\beta_2 \qquad i = 1,\dots,N; \quad t = 1,\dots,T, \\ y_{it} &= 0, \quad \text{otherwise} \end{aligned} \tag{3}$$

where y_{it} is the i^{th} farmers amount of herbicide use at time *t*, y_{it}^* is the unobserved latent variable of y_{it}, x_{it} is a vector of exogenous variables, β_1 is a $K \times 1$ vector of estimated parameters, and e_{it} is a random error term assumed to be jointly-distributed normal over *t* with a mean vector of zero and variance-covariance matrix Σ_i and independent in u_i. In addition, λ_{it} represents the inverse mills ratio (IMR) (Heckman, 1979) and β_2 is the estimated coefficient of IMR. Inclusion of the IMR corrects censoring bias that would arise from excluding non-users in the Tobit model. It also corrects for sample selection bias that would occur as a result of dropping at least one exogenous variable that is present in Equation 2 (Probit) from the estimation of Equation 4 (Tobit) (Vella, 1998). IMR is based on the predicted adoption estimates from Equation 2, and is derived as $\varphi(\alpha' w_i)/\theta(\alpha' w_i)$ where φ is the probability density function and θ is the cumulative distribution function of the standard normal distribution—see Heckman (1979) for a detailed discussion.

Using this censoring rule, the latent variable y_{it}^{*} is estimated by a regression equation described as:

$$y_{it}^{*} = x_{it}\beta_1 + \lambda_{it}\beta_2 + e_{it}, \tag{4}$$

In this approach, $y_{it} = 0$ is the corner solution to the farmer's utility maximization problem. Unlike in the estimation procedure of Dong et al. (2001), in this model $y_{it} = 0$ only denotes a typical corner solution driven by economic factors. All observations with zero outcomes due to non-adoption are no longer included in this estimation. This means that any changes in the economic variables that are included in the model (e.g. price of herbicide) will not induce non-users of herbicides to apply chemicals. Both the random-effects Tobit and cross-section Probit models are estimated using the maximum likelihood estimation (Wooldridge, 2002).

3. Data source and model variables

Panel data regarding herbicide use in rice production in the Philippines is obtained from the Rice-Based Farm Household Survey (RBFHS) that is conducted every five years by the Bureau of Agricultural Statistics (BAS) and Socioeconomics Division of PhilRice. The data set used in this study includes six of these surveys: the wet seasons of 1996, 2001, and 2006 and the dry seasons of 1997, 2002, and 2007. The RBFHS in 1996–97 covered the rice production and input use of 30 major rice-producing provinces, while the 2001–02 and 2006–07 surveys covered 33 provinces from different regions of the Philippines. The data set represents around 70% of the country's total rice area in each year, which makes it easier to generalize the findings to the national level.

The farm households that are included in the data set for each province are randomly selected from major irrigated and rainfed lowland villages using a two-stage sampling selection procedure (PhilRice, 1997). The first stage randomly selects a village. The second stage selects a farm-household using the "right coverage method". This method is used to ensure samples are randomly selected, even without a complete list of farmers in the village. Based on six rounds of survey, a total of 11,898 observations (approximately 2000 individual farmers in each round)) form the sample. Around 4,737 data points (40% of the sample) report no herbicide use on their farms. The zero outcomes for herbicide use are comprised of two components: (a) a non-user (non-adoptor) for all periods, and (b) a user but one who decided not to spray herbicides in any period (a typical corner solution). On the other hand, treating samples in terms of an individual farmer, the total sample size is 3,864. Of this total, about 28% of individual farmers did not spray herbicides in the time period covered by the survey.

Table 1 presents the descriptions and summary statistics of all the variables that are used in the analysis. It also shows the expected influences (as indicated by the positive and negative signs) of the explanatory variables on herbicide use decisions. The expected sign of some variables (e.g. age) are indeterminate because past research indicates that they can have positive or negative impacts. The unobserved latent variables that are used in the models are dependent on the type of regression employed. In the adoption model, a discrete latent variable of herbicide use (adopt) is generated, taking on a value of 1 if the farmer sprayed herbicides for at least one survey period and 0 if the farmer does not use herbicides in all survey periods (1996 to 2007). In contrast, in the regression focussed on the determinants of the level of herbicide use, two latent variables are defined: (a) herbicide expenditure (hexp), and (b) the amount of active ingredient of herbicide used (herbai). Herbicide expenditures are adjusted for inflation using the Philippines' Retail Price Index (RPI) for chemicals, with 1978 defined as the base year (NSO, 2008). On the other hand, the amount of active ingredient (a.i.) of herbicide applied by the farmer is expressed in terms of kilogram (kg) per ha per crop.

In the intensity model, dummy variables for different years are included to capture time effects, with 1996 set as the base year. However, the year effect is presented in a different way in the adoption model. Since samples in the adoption model are reported for individual farmers, the interpretation of dummy variables representing individual years is meaningless. Thus, a single time effect capturing the total probability of being a user over T time periods is generated using the following procedure. A separate random-effects Probit model with a latent variable taking the value of 1 if a respondent is a user of herbicide and 0 if a respondent is a non-user is first estimated using only dummy variables for the year as the explanatory variables. The predicted values from the Probit estimation are then generated and these values are used in calculating the total probability of adoption (tpa) expressed in log values. The values of the "tpa" parameter capture the effect of the number of times an individual farmer appears in the survey period in the predicted adoption estimates.

Table 1. Descriptions, summary statistics, and expected signs for variables in the model.

Variable	Descriptions	C[a]	CV[b] Mean	BV[c] Percentage		ES[d]
Dependent variable						
adopt	Value 1 if user of herbicide, 0 otherwise			1=60	0=40	
hexp	Average amount of herbicide sprayed (in PHP ha^{-1})		0.3			
herbai	Amount of herbicide a.i. applied (kg a.i. ha^{-1})		0.4			
Independent variable						
Labor and human capital						
age	Age of the farmer (years)	a,b	50.2			+/-
sex	Value 1 if female, 0 otherwise	a,b		1=9	0=91	+
fexp	Number of years in rice farming	a,b	23.2			+
hhsize	Number of total household members	a,b	5.4			+/-
forg	Value 1 if member of a farm organization, 0 otherwise	a,b		1=45	0=55	+/-
ftrain	Value 1 if attended a rice training, 0 otherwise	a,b		1=45	0=55	+/-
educ	Number of years in school	a,b	7.3			+/-
Land characteristics						
tstat	Value 1 if farmer owns a farm, 0 otherwise	a,b		1=51	0=49	+
area	Area planted to rice (in hectare)	a,b	1.2			+/-
Infrastructure						
irrig	Value 1 if irrigated, 0 otherwise	a,b		1=68	0=32	+
dist	Distance of farm to the nearest market (km hr^{-1})	a,b	6.9			+
Type of rice technology						
seed	Value 1 if certified seeds, 0 otherwise	a,b		1=19	0=81	-
cropes	Value 1 if transplanted, 0 otherwise	a,b		1=70	0=30	-
fert	Amount of nitrogen (N) applied (in kg ha^{-1})	b	69.5			+
insec	Amount of insecticide applied (in kg a.i ha^{-1})	b	0.2			+
Economic variable						
price	Average price of herbicide (in PHP ha^{-1})	b	0.4			-
income	Total annual household income (in thousand PHP)	b	0.9			+
credit	Total amount borrowed (in thousand PHP)	b	0.0			+
wage	Price of labor in real terms (in PHP day^{-1})	b	137.4			+
mwage	Average of price of labor (in PHP day^{-1})	b	137.4			+
Adoption-related variable						
imr	Ratio of normal density function of adoption predicted probability (app) to normal probability	b	0.4			+

[a] C = category : a= factors that affect the adoption of herbicide use; b = factors that affect the intensity of herbicide use. [b] CV = continuous variable. [c] BV = binary variables. [d] ES = expected

Table 1 cont. Descriptions, summary statistics, and expected signs for variables in the model.

Variable	Descriptions	C[a]	CV[b] Mean	BV[c] Percentage		ES[d]
Respondent dummy						
fdum	Value 1 if farm-owner is the respondent, 0 otherwise	a,b		1=73	0=27	+
Year dummies						
1996	Value 0 if 1996 (base year)					
1997	Value 1 if 1997, 0 otherwise	b		1=20	0=80	+
2001	Value 1 if 2001, 0 otherwise	b		1=20	0=80	+
2002	Value 1 if 2002, 0 otherwise	b		1=20	0=80	+
2006	Value 1 if 2006, 0 otherwise	b		1=20	0=80	+
2007	Value 1 if 2007, 0 otherwise	b		1=10	0=90	+
tpa	Year effect in adoption (in log values)	a	-0.1			+
Regional dummies						
reg3	Value 0 if Central Luzon (base region)					
reg1	Value 1 if Ilocos Region, 0 otherwise	a,b		1=15	0=85	-
reg2	Value 1 if Cagayan Valley, 0 otherwise	a,b		1=10	0=90	-
reg4	Value 1 if Southern Tagalog, 0 otherwise	a,b		1=10	0=90	-
reg5	Value 1 if Bicol Region, 0 otherwise	a,b		1=15	0=85	-
reg6	Value 1 if Western Visayas, 0 otherwise	a,b		1=5	0=95	+
reg7	Value 1 if Central Visayas, 0 otherwise	a,b		1=15	0=85	-
reg8	Value 1 if Eastern Visayas, 0 otherwise	a,b		1=10	0=95	-
reg9	Value 1 if Western Mindanao, 0 otherwise	a,b		1=10	0=90	+
reg10	Value 1 if Northern Mindanao, 0 otherwise	a,b		1=5	0=95	+
reg11	Value 1 if Southern Mindanao, 0 otherwise	a,b		1=10	0=90	+
reg12	Value 1 if Central Mindanao, 0 otherwise	a,b		1=10	0=90	+
reg13	Value 1 if ARMM, 0 otherwise	a,b		1=5	0=95	-
reg14	Value 1 if Caraga Region, 0 otherwise	a,b		1=10	0=90	+

[a] C = category : a= factors that affect the adoption of herbicide use; b = factors that affect the intensity of herbicide use. [b] CV = continuous variable. [c] BV = binary variables. [d] ES = expected sign.

The explanatory variables in the models are tested for the presence of imperfect multicollinearity and heteroscedasticity. To detect problems arising from multicollinearity, the variance inflation factor (VIF) (Baum, 2006) is estimated. As a rule of thumb, values of VIF greater than 10 are often taken as a signal that the variables are collinear. The average real price of labor (as represented by "mwage") is the only variable that has a VIF value that is greater than 10 (15.25) and thus it is removed from the model. Pearson's correlation coefficient is also used to investigate the degree of association among the variables. Result show that the "age" and farming experience (as represented by "fexp") of farmers are highly correlated and thus using both variables in the models would inflate the standard errors. Thus, only "age" is retained in both models and "fexp" is removed. Moreover, "robust" and “bootstrapped standard error” commands in STATA program are used in estimating the cross-section Probit and random-effects Tobit models to overcome any inherent heteroscedasticity (Baum, 2006).

4. Results and discussion

4.1 Base results

Table 2 presents the estimated parameters for the adoption and level of herbicide use models and their corresponding standard errors. Columns 2 and 3 present the results of the cross-section binary Probit model for adoption of herbicide, while Columns 4 to 7 report the results of the random-effects Tobit regressions for the level of herbicide use using the two unobserved latent variables: (a) herbicide expenditure, and (b) the amount of herbicide active ingredient applied.

The results for the Probit (adoption) regression show that the adoption model is significant at the 0.01 level based on a model chi-square statistic of 1056.74 with 27 degrees of freedom. The calculated McFadden R^2 of the model is 0.32, with 80% of the responses predicted correctly. These statistics show that the adoption model that is used in this study is reasonably accurate, as it performs well in explaining the factors that influence farmers’ decision to use herbicides. The two random-effects Tobit (intensity) regressions also fit well for the models estimating the determinants of the level of herbicide use. The models are statistically significant at the 0.01 level using the Wald test based on a model chi-square statistic of 1865.20 for herbicide cost (Tobit Model 1) and 319.23 for the amount of herbicide active ingredient used (Tobit Model 2).

Results of the regressions in general show that the decision to use herbicides is driven by different factors to those that explain the decision of how much to apply. Specifically, in the labor and human capital group of variables, household size (as represented by “hhsize” $(\rho < 0.01)$) has the expected sign and significantly influences the adoption of herbicide. However, this variable is not significant in estimating herbicide expenditure (Tobit Model 1) or the amount of active ingredient of herbicide applied (Tobit Model 2). This implies that farmers with larger families are more likely to adopt herbicides for controlling weeds in their rice fields, but once the farmers decide to use herbicides, their decisions regarding the quantity of herbicide to be applied are no longer affected by their “hhsize”. The “age” of the

Table 2. Probit and Tobit parameter estimates of herbicide use.

Variable	Adoption (Probit Model)			Herbicide (Tobit Model 1)			Herbicide a.i. (Tobit Model 2)		
	Coefficient		S.E.[a]	Coefficient		S.E.	Coefficient		S.E
constant	1.253	**	0.217	0.223	*	0.140	-0.118		1.119
age	-0.004	***	0.002	-0.001		0.000	-0.001		0.003
sex	0.097		0.096	0.002		0.015	0.004		0.086
hhsize	0.033	***	0.012	-0.002		0.002	-0.004		0.016
forg	0.016		0.059	0.001		0.012	0.095	*	0.055
ftrain	0.033		0.059	0.020	*	0.011	-0.006		0.066
educ	0.007		0.009	0.002		0.002	0.014		0.001
tstat	0.176	***	0.053	0.017	*	0.010	0.081		0.078
area	0.304	***	0.037	-0.009	*	0.006	0.031		0.036
irrig	0.172	***	0.055	0.007		0.011	0.000		0.109
dist	-0.001		0.002	0.001		0.001	0.001		0.004
seed	0.103		0.074	-0.001		0.012	0.030		0.078
cropes	-0.830	***	0.074	-0.182	***	0.015	-0.589	***	0.124
fert				0.001	***	0.000	0.001	*	0.001
insec				0.001		0.001	0.019		0.041
price				0.301	***	0.040	-1.567	***	0.304
income				0.013	**	0.006	0.075	**	0.034
credit				0.111	*	0.068	0.281		0.406
wage				-0.000		0.001	0.007		0.007
imr				0.089	***	0.030	0.326	*	0.209
fdum	0.084		0.069	0.028	**	0.013	0.102		0.068
1997				-0.037	**	0.015	-0.283		0.178
2001				-0.036	**	0.015	-0.238	**	0.117
2002				-0.190		0.018	-0.165		0.150
2006				-0.001		0.015	-0.286	**	0.135
2007				-0.028	*	0.015	-0.410	***	0.137
tpa	2.989	***	0.185						
reg1	-0.421	***	0.106	-0.142	***	0.033	-0.762	**	0.375
reg2	-0.354	***	0.104	-0.080	**	0.036	-0.361		0.350
reg4	0.066		0.098	0.070	**	0.028	-0.021		0.213
reg5	-0.390	***	0.104	-0.051		0.045	-0.218		0.413
reg6	0.766	***	0.246	-0.030		0.050	0.017		0.386
reg7	-1.863	***	0.168	-0.394	***	0.089	-0.524		0.832
reg8	-1.207	***	0.104	-0.304	***	0.054	-1.260	*	0.672
reg9	0.150		0.112	0.043		0.042	0.249		0.409
reg10	0.030		0.155	-0.006		0.044	-0.140		0.286
reg11	0.751	***	0.120	0.073		0.047	0.337		0.413
reg12	0.562	***	0.168	0.033		0.039	-0.151		0.297
reg13	-0.323	**	0.134	-0.099	**	0.045	0.302		0.754
reg14	0.587	***	0.155	0.072	*	0.043	0.112		0.375
Log likelihood	-1565.71			-5260.86			-19415.30		
McFadden R^2	0.317								
Model Chi^2 (p-value)	1056.74 (0.000)			1865.20 (0.000)			319.23 (0.000)		
% Predicted Correctly[b]	80.41								

*** significance at 1%, ** significance at 5% and * significance at 10% levels. [a] S.E. stands for standard errors. [b] Ratio of sensitivity to specificity. Sensitivity is the percentage of users identified correctly while specificity is the percentage of non-users classified correctly.

farmer has a negative sign and significantly influences both the decision to adopt $(\rho < 0.05)$ and herbicide expenditure $(\rho < 0.10)$, but not the amount of active ingredient applied. A negative sign indicates that young farmers are more likely to adopt and spend more on herbicides. This could represent a greater reluctance for older farmers to adopt new technologies given their preference for more traditional methods of weed control, such as flooding and hand-weeding.

Participation in training, as represented by "ftrain" $(\rho < 0.10)$, has a positive significant impact on herbicide expenditure (Tobit Model 1), but is not statistically related to the adoption decision and amount of active ingredient applied. Thus, those farmers who have attended rice-production training events held throughout the Philippines typically apply more herbicides. A positive relationship between "ftrain" and herbicide expenditure could arise because many of the training events attended by the farmer respondents are sponsored by the chemical companies who produce and sell the herbicides.

Within the land characteristics category, both tenurial status (as represented by "tstat") and farm area (as represented by "area") significantly affect both adoption $(\rho < 0.01)$ and herbicide expenditure decisions $(\rho < 0.10)$. As hypothesized, farmers who own their farms are more likely to use herbicides. This is primarily because farmers who do not own their land may be hesitant to adopt a new technology due to capital constraints and apprehension that this technology may not succeed (Casiwan et al., 2003). In addition, farmers who have large farm areas tend to adopt herbicides and incur lower costs per hectare. The inverse relationship of farm area to herbicide expenditure implies that economies of scale exist in regards to herbicide use in rice crops in the Philippines.

Under the infrastructure category, the presence of irrigation (as represented by "irrig") significantly influences the adoption decision $(\rho < 0.01)$, but not the level of herbicide use. This highlights the importance of water availability as a determinant of chemical use because application of herbicides is more effective if water is controlled. Moreover, the distance of farm to market (as represented by "dist") appears to be an unimportant variable in herbicide use decisions in this study. This implies that farmers with easy access to input markets behave essentially the same as farmers who have less access to input markets. The quality of road infrastructure or available transport, which is not captured by the market distance variable, perhaps could be a more important determinant of herbicide use, but were not incorporated here due to a lack of data.

Among the variables relating to the type of technology category, the method of crop establishment (as represented by "cropes") is a significant factor $(\rho < 0.01)$ in both decisions. As expected, results show that more farmers who direct-seed rice crops use herbicides than those who transplant their crops. Also the herbicide applications of farmers who practice direct-seeding are also relatively high. This supports the hypothesis that herbicide use varies significantly across the establishment methods that are typically used to plant rice crops.

Under the group of technology variables, the amount of nitrogen fertilizer applied (as represented by "fert") is also a significant predictor of both herbicide expenditure $(\rho < 0.01)$ and the amount of active ingredient applied $(\rho < 0.10)$. This may be because weeds establish and grow more easily in a nitrogen-rich soil (Ampong-Nyarko and De Datta, 1991). This finding is consistent with the recommendation to cease or delay fertilizer application to limit weed growth in rice farming systems (De Datta and Baltazar, 1996).

The price of herbicides (as represented by "price") is very important in determining herbicide use, in line with basic economic theory that states that the demand for herbicide would usually be expected to be inversely related to its market price. Tobit Model 2 is consistent with this theory, implying that as the price of herbicide goes up, the amount of active ingredient applied decreases. On the other hand, the estimated effect of "price" in Tobit Model 1 is less clear theoretically, as price is also a component of the derived herbicide expenditure variable. The fact that an increase in herbicide price decreases herbicide expenditure indicates that farmers demand for herbicides is 'inelastic', meaning that the percentage change in use is less than the percentage change in prices (Table 2).

Concerning the annual household income (as represented by "income"), results show that it is positively associated and significantly influences $(\rho < 0.01)$ the herbicide use measured in both models. It appears that the higher the capacity of farmers to meet a cash requirement on purchasing inputs, the higher the quantity of herbicide use. A similar effect on herbicide use is observed relating to the amount of production loan or access to "credit" that a farmer has, although its influence is not significant in determining the amount of active ingredient that is used (Tobit Model 2). Furthermore, the real price of labor (as represented by "wage") is insignificant in both herbicide use models. This means that once farmers decide to use herbicides, their decisions regarding the quantity to be applied are only weakly affected by the "wage".

In terms of participation-related variables, the coefficients of IMR are significant in both Tobit models. This implies that removing this variable would result in biased estimates due to misspecification error. Moreover, the "fdum" variable that is incorporated in the model to qualify the reliability of information provided by each producer is only significant $(\rho < 0.01)$ in determining herbicide expenditure (Tobit Model 1), although its impact tends to be small overall. Observed insignificant effects pertaining to the "fdum" variable in the adoption decision and the amount of active ingredient used imply that the information given by the farm-owner and other non farm-owner respondents (e.g. tenant, family member) are very similar. This is likely to be true, as this information is easier to recall compared to that regarding total herbicide expenditure.

The "tpa" variable represents the year effects for the adoption decision (see Section 3). It has a significant influence on whether a farmer uses herbicides. Its positive effect (Table 2) implies that an individual farmer who appears a greater number of times in the survey periods is more likely to be a user of herbicides. In fact, the "tpa" is significantly correlated $(r = 0.73, \rho < 0.01)$ with the number of times that the farmer is interviewed across the whole survey period.

Quantity of herbicide use varies between cropping years, as indicated by the year dummies. Relative to the herbicide used in 1996, results show that herbicide use generally fell. This trend is more evident in the amount of active ingredient applied, as lower application rates are now commonly observed in rice fields, despite no decrease in weed control effectiveness, due to the increasing potency of herbicides. Moreover, results reported for the regional dummy variables show that region is a key determinant of herbicide use, but its impact is highly variable. For example, estimates reported in Table 2 demonstrate that the use of herbicide in Central Luzon is significantly higher than in Ilocos, Cagayan Valley, Bicol, Central and Eastern Visayas, and ARMM. However, it appears to be lower than in Western Visayas, Southern and Central Mindanao, and Caraga. These differences could be attributed to specific localized problems with crop weeds, regional price differences of herbicides, and the regional activities of chemical dealers.

4.2 Economic significance of estimated parameters

Since the statistical significance presented above does not necessarily correspond with economic significance (McCloskey and Ziliak, 1996), an estimated measure of the impact of each variable in the Tobit regression is also presented. Results of adoption estimates here are not the same as those reported in Table 2 because of the inclusion of all of the explanatory variables in the Tobit model. Interpretation is only focussed on the estimates of Tobit Model 1 because it appears that it gives the best fit for the model, has more significant explanatory variables, and has higher values of log likelihood and chi-square parameters, compared to Tobit Model 2. Two indicators of economic significance are used in this study.

The first indicator is the marginal effect or point elasticity, which represents the percentage change in herbicide use per percentage change in each of the independent variables. The marginal effects are estimated using the "elasticity decomposition framework" developed by McDonald and Moffitt (1980) for Tobit generated coefficients and parameter estimates are generated using STATA program (Baum, 2006). The estimates of marginal effects are provided in Table 3. Column 2 presents the elasticity of probability of participation in the market, while Columns 4 and 6 respectively demonstrate the elasticity of herbicide use conditional and unconditional on participation.

Results show that of all the significant explanatory variables (economic and non-economic) identified in the general analysis (Table 2), only the "price", "credit", and "cropes" are found to have significant impacts on herbicide use. The maximum likelihood estimates reported in Table 3 show that conditional on herbicide use, a 1% change in the average price of herbicides would increase the amount of herbicide expenditure by approximately 0.16% and about 0.24% for the probability of adopting the herbicide. If the farmer uses direct-seeding for crop establishment, their herbicide expenditure and the likelihood of adopting herbicide use is respectively higher by 10 and 14%, compared to if transplanting was used. In addition, a 1% increase in the average amount of production loan would raise the expenditure on herbicide by about 0.06% and about 0.09% for the probability of using herbicide. It is interesting to note that "income", which is found to be statistically significant, has a low elasticity in determining herbicide use (Table 3). This suggests that, although the effect of a one-dollar change in income is low, the range of income levels in the sample is large enough to result in statistical significance.

Table 3. Marginal effects (elasticities) of Tobit parameter estimates of herbicide use.

Variable	Adoption effect[b]			Conditional effect[b]			Unconditional effect[b]		
	Elasticity		S.E.[c]	Elasticity		S.E.	Elasticity		S.E.
age	-0.001	*	0.00	-0.001	*	0.000	-0.001	*	0.003
sex[a]	-0.002		0.01	-0.001		0.008	-0.002		0.011
hhsize	-0.002		0.00	-0.001		0.001	-0.002		0.002
forg[a]	0.001		0.00	0.001		0.006	0.001		0.009
ftrain[a]	0.016	*	0.00	0.011	*	0.006	0.015	*	0.009
educ	0.002		0.00	0.001		0.001	0.002		0.001
tstat[a]	0.014	*	0.00	0.009	*	0.006	0.013	*	0.008
area	-0.007	*	0.00	-0.005	*	0.003	-0.007	*	0.004
irrig[a]	0.005		0.00	0.004		0.006	0.005		0.008
dist	0.001		0.00	0.000		0.000	0.001		0.000
seed[a]	-0.001		0.01	-0.000		0.006	-0.001		0.009
cropes[a]	-0.136	***	0.01	-0.102	***	0.008	-0.141	***	0.011
fert	0.001	***	0.00	0.001	***	0.000	0.001	***	0.000
insec	0.005		0.00	0.003		0.004	0.004		0.005
price	0.236	***	0.03	0.163	***	0.022	0.228	***	0.031
income	0.010	**	0.00	0.007	**	0.003	0.010	**	0.005
credit	0.087	*	0.05	0.060	*	0.037	0.084	*	0.052
wage	-0.000		0.00	-0.000		0.000	-0.000		0.000
imr	0.070	***	0.02	0.048	***	0.016	0.068	***	0.023
fdum[a]	0.022	**	0.01	0.015	**	0.007	0.021	**	0.010
1997[a]	-0.030	**	0.01	-0.020	**	0.008	-0.028	**	0.011
2001[a]	-0.028	**	0.01	-0.020	**	0.008	-0.027	**	0.011
2002[a]	-0.015		0.01	-0.010		0.009	-0.142		0.013
2006[a]	-0.001		0.01	-0.000		0.008	-0.000		0.011
2007[a]	-0.022	*	0.01	-0.015	*	0.008	-0.021	*	0.011
reg1[a]	-0.122	***	0.03	-0.071	***	0.015	-0.099	***	0.021
reg2[a]	-0.066	**	0.03	-0.042	**	0.018	-0.059	**	0.026
reg4[a]	0.052	***	0.02	0.039	**	0.016	0.054	**	0.022
reg5[a]	-0.042		0.03	-0.027		0.023	-0.038		0.032
reg6[a]	-0.024		0.04	-0.016		0.026	-0.023		0.037
reg7[a]	-0.371	***	0.08	-0.164	***	0.027	-0.228	***	0.034
reg8[a]	-0.280	***	0.05	-0.135	***	0.019	-0.191	***	0.026
reg9[a]	0.033		0.03	0.024		0.024	0.033		0.033
reg10[a]	-0.005		0.03	-0.003		0.024	-0.004		0.033
reg11[a]	0.054	*	0.03	0.041		0.027	0.057		0.037
reg12[a]	0.025		0.02	0.018		0.022	0.026		0.031
reg13[a]	-0.084	**	0.04	-0.050	**	0.022	-0.071	**	0.031
reg14[a]	0.053	*	0.03	0.040		0.025	0.056		0.034

[a]Marginal effects for the dummy variables are interpreted as the percentage change in herbicide use in response to 0/1 change in dummy variables. [b]Adoption effect, conditional and unconditional effects are evaluated with respect to X_i at $\overline{X_i}$. [c] S.E. stands for standard errors. *** significance at 1%, ** significance at 5% and * significance at 10%.

The second measure of economic significance that is used in this study is the "absolute-change" indicator developed by Abadi Ghadim et al. (2005). This indicator incorporates the influence of both elasticity and sample variance. The importance of including variance in the estimates of impact is to capture the fact that independent variables with wider ranges of values have a larger absolute influence on the dependent variables. In this approach, the predicted probability of adoption (*Prob*) and level of intensity of herbicide use (*Intensity*) are computed by setting each continuous variable to a value two sample standard deviations above the sample mean ($Prob^+$ and $Intensity^+$) and below the sample mean ($Prob^-$ and $Intensity^-$), and setting all other variables to their means. The absolute-change indicator for the probability of adoption (ΔP) is the difference between the $Prob^+$ and $Prob^-$ parameters. The absolute-change indicator for the probability of intensity of use (ΔI) is the difference between the $Intensity^+$ and $Intensity^-$ parameters. In this study, absolute-change is calculated only for continuous variables. The estimated values of the indicators for Tobit Model 1 are shown in Table 4.

Table 4. Indicators of absolute-change for the probability of adoption and intensity of herbicide use.

Variable	Mean	SD	Prob+	Prob-	ΔP	Intensity+	Intensity-	ΔI
age	49.93	13.11	0.74	0.77	0.03	0.32	0.35	0.33
hhsize	5.53	2.30	0.75	0.76	0.02	0.32	0.34	0.02
educ	7.50	3.24	0.77	0.74	0.03	0.35	0.32	0.03
area	1.28	1.23	0.74	0.76	0.02	0.31	0.35	0.04
dist	7.15	8.22	0.77	0.75	0.02	0.34	0.32	0.02
fert	73.51	48.07	0.82	0.67	0.15	0.42	0.25	0.17
insec	0.22	0.87	0.77	0.75	0.02	0.34	0.32	0.02
price	0.42	0.25	0.85	0.65	0.20	0.46	0.24	0.22
income	1.01	1.11	0.78	0.73	0.05	0.36	0.31	0.05
credit	0.04	0.10	0.78	0.74	0.04	0.36	0.32	0.04
wage	139.55	20.78	0.74	0.77	0.03	0.32	0.35	0.03

ΔP is the absolute change in probability adoption = ($Prob^+$ - $Prob^-$)
ΔI is the absolute change in intensity of herbicide use = ($Intensity^+$ - $Intensity^-$)

Similar to the marginal effect estimates, results of calculated absolute-change indicators show that the market price has the largest impact on herbicide adoption and intensity of use. The other variable that stands out in these results is fertilizer use. This is interesting given the low elasticity for fertilizer (Table 3) and reflects the high sample variance for this variable. This result for fertilizer application supports the results of regression analysis reported in Table 2. Also of interest is that the amount of production loans taken by producers was found to have the second largest marginal elasticity value among the continuous variables (Table 3), but is only the fourth most-important determinant of herbicide use when sample variance is considered (Table 4). This demonstrates the importance of not focusing solely on elasticities when examining the importance of independent variables.

5. Conclusions

In this research we examined factors affecting the adoption and intensity of use of herbicides in Philippine rice farming systems. The cross-sectional double-hurdle model is extended to deal with panel data through the employment of a cross-sectional Probit procedure for the adoption stage and a random-effects Tobit procedure for the level of use stage. The advantage of using a panel double-hurdle model is that it allows separate analysis of what determines the adoption and use of herbicides.

Results broadly reveal differences in the key drivers of the adoption and use decisions. The age of the farmer, household size, and irrigation status are the significant factors influencing the decision of farmers to use herbicides. Once the farmers decide to use herbicides, their decisions regarding the quantity of herbicide to be applied are no longer affected by these factors. On the other hand, rice production training or seminars attended by producers, and level of fertilizer use only play an influential role in determination of the quantity of herbicide to be used. Economic variables such as price of herbicide, total income of farmers, and production loan or credit are also highly significant determinants of the intensity of herbicide use.

Land ownership, farm area, and method of crop establishment used (direct-seeded or transplanted) are significant predictors in both the adoption and herbicide use decisions. Regional differences in herbicide demand also exist. These differences could be attributed to locational crop-weed problem situations and price differences of herbicides. It could also be the result of regional activities of chemical dealers.

Overall, the research has improved our understanding of herbicide use in the Philippines. It highlights the complexity of the issue, with different variables influencing decisions about whether to adopt herbicides at all, and if so how much herbicide to use. The insights generated should be of value to agricultural extension agents, and to policy makers considering measures to avoid the over-use of herbicides.

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References

Abadi Ghadim, A., Pannell, D.J. and Burton, M.P. (2005). Risk, uncertainty and learning in adoption of a crop innovation. Agric. Econ. 33, 1–9.

Abera, H. (2008). Adoption of improved tef and wheat production technologies in crop livestock mixed systems in Northern and Western Shewa Zones of Ethiopia, PhD Thesis, University of Pretoria, Ethiopia.

Ampong-Nyarko, K. and De Datta, S.K., 1991. A Handbook for Weed Control in Rice. International Rice Research Institute (IRRI), Manila, Philippines.

Baltagi, H., 1995. Econometric Analysis of Panel Data. John Wiley and Sons, Chichester.

Baum, C., 2006. An Introduction to Modern Econometrics Using STATA. A Stata Press Publication, StataCorp LP, College Station, Texas.

Blundell, R. and Meghir, C., 1987. Bivariate alternatives to the Tobit model. J. Econometrics 34, 179–200.

Brouhle, K. and Khanna, M., 2005. Determinants of participation versus consumption in the Nordic Swan Eco-labeled market. Available at http://ideas.repec.org/p/ags/aaea05/19443.html (accessed 25 Oct 2010).

Casiwan, C.B., Janaiah, A., Francisco, S.R., Hossain, M., Narciso, J., Cabrera, E. and Hidalgo, F.C., 2003. Hybrid rice cultivation in the Philippines: early farm-level experiences. Econ. and Political Weekly 38, 2502–2508.

Cragg, J.G., 1971. Some statistical models for limited dependent variables with application to the demand for durable goods. Econometrica 39, 829-844.

De Datta, S.K. and Baltazar, A.M., 1996. Integrated weed management in rice in Asia. In: Naylor, R. (ed.), Herbicides in Asian Rice: Transitions in Weed Management. Palo Alto (California): Institute for International Studies, Stanford University and Manila (Philippines): International Rice Research Institute, pp. 145–166.

Dong, D., Chung, C. and Kaiser, H., 2001. Panel data double-hurdle model: an application to dairy advertising. In: Proceedings of the AAEA Annual Meeting, 5–8 August 2001, Chicago, USA.

Greene, W.H., 2003. Econometric Analysis, fifth edition. Prentice Hall, New Jersey.

Heckman, J.J., 1979. Sample selection bias as a specification error. Econometrica 47, 153–161.

Johnson, D.E. and Mortimer, A.M., 2005. Issues for integrated weed management and decision support in direct-seeded rice. In: Toriyama, K., Heong, K.L. and Hardy, B. (eds.), Rice is Life: Scientific Perspective for the 21st century. Proceedings of the World Rice Research Conference. IRRI and Japan International Research Center for Agricultural Sciences (CD-ROM), 4–7 November 2004, Tokyo and Tsukuba, Japan, pp. 211–214.

Llewellyn, R.S., Lindner, R.K., Pannell, D.J. and Powles, S.B., 2007. Herbicide resistance and the adoption of integrated weed management by Western Australian grain growers. Agric. Econ. 36, 123–130.

Maddala, G.S., 1987. Limited dependent variable models using panel data. J. Hum. Resources 22, 307–338.

McCloskey, D.N. and Ziliak, S.T., 1996. The standard error of regressions. J. Econ. Literature 34, 97–114.

McDonald, J.F. and Moffitt, R.A., 1980. The uses of tobit analysis. Rev. Econ. and Statistics 62, 318–321.

Newman, C., Henchion, M. and Matthews, A., 2003. A double-hurdle model of Irish household expenditure on prepared meals. App. Econ. 35, 1053–1061.

NSO, 2008. National Statistics Office (NSO), Retail Price Index. Available at http://www.census.gov.ph (accessed 20 October 2008).

Pannell, D.J., Marshall, G.R., Barr, N., Curtis, A., Vanclay, F. and Wilkinson, R., 2006. Understanding and promoting adoption of conservation practices by rural landholders. Aus. J. Exp. Agric. 46, 1407–1424.

PhilRice, 1997. Monitoring of rice-based farm households in strategic rice areas (A BAS-PhilRice Project) Manual Operations. PhilRice, Nueva Ecija, Philippines.

Pingali, P.L., Hossain, M. and Gerpacio, R.V., 1997. Asian Rice Bowls: The Returning Crisis? CAB International in association with IRRI.

Sinning, M., 2009. Determinants of savings and remittances: empirical evidence from immigrants to Germany. Rev. of Econ. of the Household.

Tobin, J., 1958. Estimation of relationships for limited dependent variables. Econometrica 26, 24–36.

Vella, F., 1998. Estimating models with sample selection bias: a survey. J. Hum. Resources 33, 127–169.

Wooldridge, J.M., 2002. Econometric Analysis of Cross Section and Panel Data. Massachusetts Institute of Technology, Cambridge, Massachusetts, London, England.

Zhang, W., Qi, Y. and Liu, Y. (2004). Forecasting trend of rice production of the world and regions. In: Fischer, T., Turner, N.C., Angus, J., McIntyre, L., Robertson, M., Borrell, A. and Lloyd, D. (eds.), New Directions for a Diverse Planet. Proceedings for the 4th International Crop Science Congress, Brisbane, Australia, 26 September–1 October 2004.