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Pesticide-handling practices: the case of coffee growers in Papua New Guinea*

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Pesticide mismanagement potentially has high risks for farmers, households living in the community and the environment. In Papua New Guinea where farming is the primary occupation, there is evidence of dangerous herbicide application methods being used by coffee growers. Using original survey data for coffee smallholders from four provinces, we assess the factors driving farmers' use of personal protective equipment when preparing and applying herbicides, and farmers' disposal of agro-chemical containers. We control for households' demographic variables and measure the impact of farmers' training in pest and disease management. We use the special regressor method to estimate binary choice models featuring an endogenous binary regressor (training). Our results show that human capital (education) and training are important drivers of farmers' pesticide-handling practices, with marginal effects estimated at 10 and 22 per cent, respectively.

Key words: farmers' practices, Papua New Guinea, pesticides, special regressor, training.

1. Introduction

Health hazards due to pesticide exposure and consumption of contaminated products are a widespread problem in the developing world (Ecobichon 2001; Wilson and Tisdell 2001). Farmers' direct exposure occurs mainly through direct dermal contact with the pesticides and ingestion, which may happen during the preparation and application of the chemicals.[1] Pesticide poisoning is more common and often more severe in developing nations for a number of reasons: one is that pesticide spraying is often performed directly by the farmer (while most farmers in industrialised countries would use a tractor). Furthermore, personal protective equipment (PPE) tends to be older and more poorly maintained in less developed countries, and in many cases farmers do not even use it. The reasons behind poorer practices can be attributed to a lack of resources for purchasing PPE, illiteracy, and lack of

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[1] Some of the most common acute poisoning effects are headaches, nausea, dizziness and convulsions.

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training and information on pesticide management. Similarly, poor legislation regulating the use of pesticides and weak law enforcing mechanisms tend to aggravate the problem (Wilson and Tisdell 2001).

In Papua New Guinea (PNG), agro-chemicals are used primarily for palm oil, sugar cane and coffee production (Bourke and Harwood 2009). The latter, which is the most important cash crop in PNG, is the focus of this study. There is evidence of widespread use of herbicides among coffee growers as well as evidence of dangerous application methods being used. As documented in Giovannucci and Hunt (2009, p. 6), herbicides are 'typically applied with backpack sprayers or from a drum by workers using no protective gear and often barefoot, thereby exposing themselves in multiple ways to toxic herbicides'. Since coffee growing involves about a third of the country's population, the population at risk due to pesticide mishandling is potentially large.

Mismanagement in the use of pesticides not only has direct adverse effects on the farmers but also may affect the environment through the pollution of soil and water sources, in particular if chemical containers are not disposed of properly. In developing countries, it is not uncommon for farmers to throw containers into the bush or clean them in water streams, hence putting at risk the population relying on unprotected water sources (see, among others, Matthews 2008 for an analysis of the practices of smallholders from 26 countries).

In this article, we study the factors influencing coffee growers' decisions about whether to wear PPE when applying herbicides and how to dispose of chemical containers, using original data from four provinces in PNG. We control for demographic factors, but our primary interest is to assess the impact of training that farmers received on pest and disease management. The vast majority of smallholders started producing coffee after the country gained independence in 1975, and land from plantations was fragmented into small plots (before independence most of these smallholders had been employed as labourers on large plantation holdings owned and managed by the British). Most of the smallholders became owner-producers without receiving adequate preparation or training on coffee cultivation practices (Giovannucci and Hunt 2009). A number of training opportunities are now offered by the Coffee Industry Corporation (CIC)[2] and by certification companies promoting sustainable farming practices. However, because of constraints in the physical access to some of the villages (due to bad infrastructure and security issues), the supply of training varies from one district to another. We exploit these differences to identify the effect of training on farmers' practices.

Since some unobserved characteristics may explain a farmer's decision to receive training and his/her pesticide-handling practices, the variable measuring training is likely to be endogenous. The usual approach in estimating binary choice models with discrete endogenous regressors is to

[2] The CIC provides both leadership and services to the PNG coffee industry.

specify two probit equations (one for the structural model and one describing the relationship between the binary endogenous variable and some exogenous variables). However, the latter (known as bivariate probit) relies on some assumptions that might be restrictive in some settings; in particular, it requires full specification of the two probit equations and the assumption of joint normality of their error terms. In this article, we use the special regressor method (Dong and Lewbel 2015), which is free from some of these assumptions.

Our article provides further evidence of the role of both human capital (education) and training on farmers' adoption of appropriate practices when handling and disposing of pesticides. A large number of studies have documented inadequate use of PPE and unsafe disposal practices among the farming population in developing countries. Even if some of these studies emphasised the importance of education and training, few have applied appropriate statistical techniques to quantify their impact. This article contributes to filling this gap using new data from PNG. Another contribution of our article is to illustrate the potential usefulness of the special regressor approach as an alternative to the more traditional bivariate probit model.

It is well recognised that training and education are efficient tools in improving farmers' practices. However, it is also acknowledged that government departments often suffer from a lack of well-trained extension agents (Ecobichon 2001). The shortage in trained extension personnel is illustrated to an extent in our sample where almost 80 per cent of all training received by the farmers was provided by either the CIC or the certification companies. The development of sustainable practices through the interventions of certification companies in poor countries might thus be a way of compensating for the lack of trained extension personnel in government agencies. As a consequence, the reduction in the health risks faced by farmers resulting from direct contact with pesticides, as well as a lower risk of waterways' contamination induced by safer chemicals disposal practices, should be accounted for as potential benefits of policies that encourage the development of schemes promoting sustainable farming practices in developing countries.

In Section 2, we present a review of the literature. In Section 3, we provide some background information and we describe the data. The model specification and methodology are presented in Section 4 and the estimation results in Section 5. Section 6 concludes.

2. Literature review

Farmers' limited knowledge about the health hazards of pesticide mishandling and inadequate use of PPE in developing countries has been documented in a number of articles (see, among others, Feola and Binder 2010; Karunamoorthi *et al.* 2011; and Wongwichit *et al.* 2012). Feola and Binder (2010) reviewed studies of farmers' use of PPE. Apart from socio-demographic variables (age, education and gender), the cost and physical discomfort of PPE, values, social norms (the desire to behave like others), past pesticide-related health issues and risk perceptions were identified as main drivers of farmers' decisions to wear PPE. We do not have information on risk perception and beliefs in our data set but hope to (partially) control for it through the socio-demographic and location characteristics of the surveyed households.

There is little statistical evidence on the role of education campaigns and training programs on the use of PPE since the focus has been more on assessing the role of training on the quantity of pesticide used. Hruska and Corriols (2002) described a two-year case study of 1,200 farmers from Nicaragua who received training in pesticide-related hazards and pesticide best practices (in terms of when and how to use it). Findings from this study showed that training induced a reduction in pesticide use and a lower exposure to pesticides. Feder *et al.* (2004) studied training provided in Indonesia through the Farmer Field Schools (FFS) program on integrated pest management knowledge and practices. The main focus of this article was on the impact of the programs on the quantity of pesticide use, rather than farmers' knowledge of pesticide-related health hazards and use of PPE. Their findings confirmed that farmers who received training changed their practices by reducing their use of pesticides, but the authors found no evidence of a significant diffusion of knowledge from trained to untrained farmers. One exception is Macharia *et al.* (2013) who studied the impact of certification for good agricultural practice (used as a proxy for training) on Kenyan farmers' pesticide-handling practices defined as a count of responses for overdose, unsafe storage, unsafe disposal and failure to wear minimum PPE. Certification was found to have no significant effect on pesticide-handling practices.

In this article, we also try to identify the impact of demographic factors and training on farmers' disposal of agro-chemical containers. Unsafe disposal of chemical containers has been confirmed by several empirical studies. Karunamoorthi *et al.* (2012) found that 77 per cent of the sampled Ethiopian farmers reused empty pesticide containers for household purposes. Macharia *et al.* (2013), in their study of Kenyan farmers, recorded a number of unsafe practices which included containers being disposed of in latrines (56 per cent) or pits (28 per cent), thrown into the bush (13 per cent) and used for household purposes (2 per cent). Hurtig *et al.* (2003) reached similar conclusions in their study conducted in the Amazon Basin of Ecuador where farmers reported reusing the chemical containers for other purposes, such as carrying vegetables, carrying water for washing clothes, using them as latrines or as drinking containers.[3] Most of these papers document farmers' practices but do not attempt to identify their drivers using appropriate statistical methods.

[3] We do not discuss here the literature which assessed the economic costs induced by the negative impact of pesticide use on farmer's health, but we refer interested readers to the proceedings on 'Economic and Health Consequences of Pesticide Use in Developing Country Agriculture' published in the *American Journal of Agricultural Economics* 76 (3).

3. Description of the background and data

Papua New Guinea has a population of just over 7 million people with, in 2011, an estimated 60 per cent of the population relying on unprotected drinking water sources.[4] The agricultural sector employs the vast majority of the population with statistics indicating that 87 per cent of the total population lives in rural areas (Rogers *et al*. 2011). The main cash crops are coffee and cocoa, which together employ approximately 50 per cent of the total labour force. Income from coffee is the most important source of cash for villagers with most of the coffee production taking place in the Western Highlands (41 per cent) and Eastern Highlands (41 per cent) provinces (Bourke and Harwood 2009).

3.1 Description of the sample

The survey data are part of a larger data set collected on a broad range of characteristics of small coffee growers in PNG. Uniquest Pty Limited prepared and conducted this survey for the Government of PNG. The data were gathered with the purpose of serving as the baseline survey for the Productive Partnership in Agriculture Project (PPAP) financed by the World Bank.[5] The sample consisted of a cross-section of households selected across the four main coffee-producing provinces: Western Highlands, Eastern Highlands, Simbu and Jiwaka.[6] The survey was undertaken in 2012 and gathered information on household demographic and socio-economic characteristics; expenditure and sales related to coffee production; household practices; access to training; health and safety on the farm; and participation in certification schemes. The data set also includes information on expenditure and income, but these variables are not considered reliable and thus were not used in our analysis (UniQuest Pty Limited, Unpubl. data, 2013). The survey of rural coffee smallholders was conducted in such a way that it included potential beneficiaries from PPAP activities. Despite not being a random sample, it is still considered to be highly representative of the smallholder coffee-producing sector.[7] The sample consisted of 800 households distributed across the four target provinces (UniQuest Pty Limited, Unpubl. data, 2013). In each province 160–240 households were surveyed (for more details of the sampling strategy, see Appendix).

[4] Source: World Health Organisation (http://www.who.int/gho/publications/world_health_statistics/2013/en/; accessed 2 Oct 2014).

[5] For further details, see: http://www.worldbank.org/projects/P110959/png-productive-partnerships-agriculture?lang=en; accessed 6 Apr 2014.

[6] Jiwaka province was originally part of Western Highlands but separated to form an independent province in 2012.

[7] PNG's National Research Institute reported that 203,025 coffee growers were found across the four provinces (UniQuest Pty Limited, Unpubl. data, 2012). Information from other sources (CIC) estimated that coffee is the main source of income for 397,772 households, which implies that the areas from which the data were collected represented more than 50 per cent of the total.

3.2 Pesticide-handling practices

Of interest in this study are farmers' practices regarding the use of PPE when handling pesticides and the disposal of chemical containers. In our sample, 96 per cent of the coffee growers applying herbicides used glyphosate.[8] Twenty-four cases of agricultural chemical injuries that required treatment by a doctor or nurse were reported. These injuries were often the consequence of direct contact with the herbicide and affected eyes or burnt legs or arms. However, such statistics only reflect acute pesticide-related health effects and do not account for possible chronic diseases that develop slowly after long and repeated exposure.

Households were asked the types of PPE they usually wore in the process of mixing and applying chemicals (up to five types could be listed by each respondent). Twenty-seven per cent of the surveyed households reported wearing some type of PPE when handling pesticides. The most popular type of equipment was long trousers (22 per cent), followed by plastic or rubber gloves (12 per cent) and protective footwear (11 per cent). Protective outer clothing, breathing masks and eye protection were the least popular with less than 4 per cent of the sampled farmers using them. For the 74 respondents reporting the use of two types of PPE, the most common combinations were gloves and long trousers (46 observations) and footwear and long trousers (21 observations). In this study, we are primarily interested in assessing farmers' awareness of risks associated with the mishandling of pesticides rather than understanding the type or the number of PPE farmers are using so, in the econometric analysis to follow, we model the decision of the farmer to wear any of the six types of PPE with a binary variable.

We now turn to the disposal of agricultural chemical containers. The proportion of households which disposed of pesticides containers by throwing them into the bush (44 per cent) was the highest. The second most popular method was to bury them (12 per cent) followed by throwing them in a river or stream (9 per cent) or burning them (9 per cent). Although a small percentage (6 per cent), some households reused the containers for household purposes. A small percentage (4 per cent) reported disposing of the containers in a natural hole, gully or crevasse and 17 per cent reported applying other methods (or did not answer the question). Although all these practices are inappropriate, we classify them into two groups depending on their potential impact on human health and the environment: burying and burning containers are the least damaging practices (Food and Agriculture Organisation 1999) and together make up one group, while throwing containers into the bush, in a

[8] Glyphosate has been classified as slightly hazardous by the World Health Organisation (2010, p. 74); see http://www.who.int/ipcs/publications/pesticides_hazard/en/; accessed 2 Oct 2014. Despite the general belief that glyphosate is inoffensive to human health, recent studies have demonstrated the opposite. Birth defects, disruption of the human hormone system and reproduction problems have been linked to exposure to glyphosate through air and water (Thongprakaisang *et al.* 2013).

natural hole, gully or crevasse, in a river or water stream, or reusing them for households' purposes are considered to be the most dangerous practices and are classified in the second group. Overall, 21 per cent of the surveyed farmers chose one of the least damaging practices (bury or burn).

In Table 1 (second and third columns), we report and compare average characteristics for the group of households which used some type of PPE and for those which did not. In the last two columns of Table 1, we compare average characteristics of households depending on their disposal practices.

On average, heads of households in all four groups were around 42 years of age and nearly 100 per cent of the household heads were men, without significant differences between the means. The proportion of uneducated household heads was significantly smaller in the group of households which wore PPE (27 per cent) than in the group of households not using PPE (37 per cent). Thirty per cent of the households disposing of containers in the least damaging way had heads without education against 36 per cent for households with the most damaging disposal practices, but the difference is not statistically significant. Moreover, the average number of children under five was significantly higher in households which stated not wearing any PPE, while the difference in means is not statistically significant when comparing households' disposal practices.

The survey also contained information on the different types of training received by each farmer. In this study, we focus on training in pest and disease management, which is commonly provided by the CIC together with certification companies in the form of workshops and field meetings. On the one hand, access to training is not significantly different between those farmers who wear PPE and those who do not. In both groups, 6 per cent of the households reported attending training in pest and disease management

Table 1 Use of personal protective equipment (PPE) and disposal of chemical containers: comparison of mean household characteristics

Variable	Households using PPE	Households not using PPE	Least damaging practices	Most damaging practices
	Mean	Mean	Mean	Mean
Age of household head (years)	42	42	43	42
Gender of household head (0 = female/1 = male)	0.97	0.96	0.95	0.96
Educational level of household head (0 = education/1 = no education)	0.27	0.37**	0.30	0.36
Number of children under five	0.55	0.67*	0.62	0.63
Training in pest and diseases management (0 = no/1 = yes)	0.06	0.06	0.09	0.05**
Remoteness index	0.09	0.24***	0.14	0.22***
Number of observations	204	557	153	577

Notes *, **, *** indicates significant differences between the means at the 10%, 5% and 1% level, respectively; n.s., not significant.

sessions. On the other hand, households with the least damaging practices reported a significantly higher percentage of heads attending training in pest and disease management (9 per cent, against 5 per cent in the other group). Finally, the average remoteness index (a higher index indicates a more remote place of living) was significantly higher for households not wearing any PPE (compared to households which did wear PPE) as well as for households with the most damaging practices (compared to households using the least damaging practices).[9]

A Pearson chi-square test of independence between the two decisions (use of PPE and disposal of chemical containers in the least damaging way) shows that the null assumption of independence is rejected at the one per cent level of significance. The proportion of households burying or burning containers is higher within the group of households wearing some PPE (30 per cent) than within the group of households not wearing any equipment (18 per cent). In the econometric analysis, however, we analyse the two decisions separately. This approach does not bias the estimated coefficients but may result in some loss of efficiency in the parameter estimates.

4. Model specification and estimation methodology

4.1 Farmers' behavioural model

We use the traditional averting behaviour model to analyse farmers' pesticide-handling practices. In the following, we describe the model underlying a farmer's decision to use PPE (*protect*), but the same would apply for the disposal of chemical containers. We assume that farmers maximise the following utility function:

$$U = U[C, H(protect)], \tag{1}$$

where H(.) is the health production function and C, a composite good (Abrahams *et al*. 2000).

The production of health (H) is assumed to depend on a farmer's decision to wear (or not) PPE and the actual health risks (π) associated with direct and indirect exposure to pesticides:

$$H = H(protect, \pi). \tag{2}$$

[9] The index of remoteness takes into account the distance that the farmer needs to walk to a Public Motor Vehicle (PMV) terminal and the time taken to travel to a purchasing centre. It is calculated as follows: ((Km travelled by PMV from village to purchasing centre*minimum time to walk to PMV terminal in minutes)*proportion of population with access to PMV from village) + ((Km travelled from PMV terminal to purchasing centre*walking time in minutes to PMV terminal)*proportion of the population walking to PMV terminal)). Uniquest Pty Ltd calculated the index of remoteness and made it available in the data set that was provided to us. We normalised this index such that it lies between zero and one, with one indicating the most remote location.

As suggested by Eom (1994), it is usually difficult for individuals to assess risks, especially risks related to pesticide exposure and ingestion through contaminated water and food; and therefore, perceived risks may differ from actual (objective) risks. Following Abrahams *et al.* (2000), we define the perceived expected level of health as:

$$H^* = H(protect, \pi^*), \tag{3}$$

where π^* represents the farmer's perceived risk. The latter is related to actual risk as follows:

$$\pi^* = \pi^*(\pi, \alpha, \beta), \tag{4}$$

with α representing the farmer's attitudes towards pesticide use and β the farmer's knowledge of pesticide-related health hazards.

We set *protect* = 1 if the farmer is using PPE and zero otherwise. The farmer will decide to wear protective equipment if:

$$U_1 = U[C, H(protect = 1; \pi, \alpha, \beta)] > U_0 = U[C, H(protect = 0; \pi, \alpha, \beta)]. \tag{5}$$

We specify the function U as linear in its parameters, β_j (j = 0, 1), and as the sum of a deterministic term ($\boldsymbol{X}'\beta_j$) and an error term of mean zero (ε_j). The household will use PPE if:

$$U^* = U_1 - U_0 = \boldsymbol{X}'(\beta_1 - \beta_0) + \varepsilon_1 - \varepsilon_0 > 0, \tag{6}$$

where $\boldsymbol{X}$ is the vector of explanatory variables. U* is a latent variable unobserved by the econometrician; only the decision (D) to wear PPE (or not) is observed. Hence, the model to be estimated is of the form:

$$D = I(\boldsymbol{X}'\beta + \varepsilon \geq 0), \tag{7}$$

meaning that D is equal to one when $\boldsymbol{X}'\beta + \varepsilon$ is positive, and zero otherwise.

In the empirical application, the vector of explanatory variables $\boldsymbol{X}$ gathers variables controlling for households' demographic and socio-economic characteristics: age of the household head, education of the household head (controlled by a dummy variable which takes the value one if the household head did not complete any schooling, and zero otherwise) and the number of children under the age of five. Risk theory indicates that as people get older they are more likely to have risk averse attitudes (Dosman *et al.* 2001), and medical evidence suggests that risk aversion correlates to healthier habits (van der Pol and Ruggeri 2008). Therefore, we expect a positive relationship between age and the likelihood of adopting better practices (i.e. wearing PPE and burying or burning containers). Education is expected to be positively correlated with knowledge so that we would expect better educated

Table 2 Summary statistics for the explanatory variables (761 observations)

Variables	Mean	SD	Min	Max
Age of the household head	42	11	19	86
Educational level of household head	0.35	0.48	0	1
Number of children under five	0.64	0.86	0	5
Training in pest and diseases management	0.06	0.23	0	1
Remoteness index	0.20	0.29	0	1
Proportion of households producing certified coffee in the district	0.11	0.31	0	1
Province dummies				
Eastern Highlands	0.26	0.44	0	1
Western Highlands	0.20	0.40	0	1
Simbu	0.24	0.43	0	1
Jiwaka	0.30	0.46	0	1

households to be better informed about pesticide-related health hazards and hence be more likely to wear protective equipment and to dispose of chemical containers in the least damaging way. We control for the number of small children in the household and make the assumption that families with young children are expected to undertake practices that reduce health risks for children, and hence adopt safer practices in general (even if figures in Table 1 suggest the opposite relationship). We also control for whether someone in the household received training in pest and diseases management and expect training to induce better pesticide-handling practices. Finally, we control for a household's location through province-specific dummy variables and the remoteness index. We hypothesise that households living in more remote villages are less well informed about health hazards and hence are less likely to wear PPE and to bury or burn chemical containers. Summary statistics of the explanatory variables are shown in Table 2.

4.2 Estimation methodology

Our purpose is to estimate two (separate) binary decision models to describe farmers' use of PPE and disposal of chemical containers. Training, which is one of the variables of interest, is likely not to be exogenous because this is primarily a farmer's decision and some unobservable factors may have influenced his/her decision to participate in training as well as his/her pesticide-handling practices. This variable is also measured using a binary indicator. The most common approach to estimating binary decision models with endogenous binary regressors is the estimation of a bivariate probit.[10] The latter, however, involves the specification and full parameterisation of an equation describing the likelihood of farmers receiving training along with some distributional assumptions on the error terms (joint normality assumption). In

[10] Control function methods are inconsistent when the endogenous variable is not continuous (Lewbel *et al.* 2012).

this study, we use the special regressor method, which is free from the above assumptions (Lewbel *et al.* 2012; Dong and Lewbel 2015).

The special regressor model has a threshold crossing form similar to the model of interest described in (7): $D = I(\boldsymbol{X}'\beta + V + \varepsilon \geq 0)$. The distinctive feature of this model is that it incorporates a single regressor V that has the following properties: (i) it enters additively in the model (with a coefficient normalised to one); (ii) it is exogenous (that is, V is conditionally independent of the error term ε); and (iii) it is continuously distributed on a large support. Instrumental variables ($\boldsymbol{Z}$) are needed to control for endogeneity. To be valid, instruments $\boldsymbol{Z}$ should satisfy the usual properties: $E(\boldsymbol{Z}\varepsilon) = 0$ and $E(\boldsymbol{Z}'\boldsymbol{X})$ has full rank. Only one special regressor V is required, whatever the number of endogenous variables. The special regressor method thus does not require the relationship between the endogenous variable and the instruments to be specified and is free from any assumptions on the joint distribution of the error term of the model of interest (ε) and the error term in the relationship between the endogenous variable and the instrument. For details on the estimation procedure, we refer readers to Lewbel *et al.* (2012) and Dong and Lewbel (2015).

The age of the household head is chosen as the special regressor. The assumption that age (as any other regressor) enters additively in the model is a very common assumption and normalising its coefficient to one does not make any difference in the calculation of marginal effects. Age is continuously distributed and can be assumed to be exogenous. The large support condition is satisfied by our data, as will be discussed in the next section. In terms of the instruments $\boldsymbol{Z}$, we consider a dummy variable which takes the value one if more than 50 per cent of the sampled households in the district produce certified coffee (our sample covers 46 districts), and zero otherwise. This variable controls for the presence of certifying companies in the district where the household lives. The presence of such companies (which is partially driven by conditions of access to the districts and their remoteness) increases the supply of training, but we assume that the impact of such companies on a household's use of PPE and choice of chemical containers disposal method is only through any training provided. Statistical tests assessing the validity of this instrument are discussed in the next section.

5. Estimation results

Marginal effects estimated using the special regressor approach are shown in Table 3.[11] Standard errors have been bootstrapped using 250 replications. The special regressor method involves the estimation of the density of the residuals of the regression of the special regressor V on $\boldsymbol{X}$ and $\boldsymbol{Z}$. Two

[11] Marginal effects are computed using the Average Index Function (see Dong and Lewbel 2015). The models were estimated using the procedure *sspecialreg* developed for Stata by Christopher F. Baum (2012): sspecialreg: Stata module to estimate binary choice model with discrete endogenous regressor via special regressor method; http://ideas.repec.org/c/boc/bocode/s457546.html.

Table 3 Marginal effects (special regressor method)

Variables	Use of PPE			Disposal of containers (least damaging practices)		
	Coef.	SE	$P > z$	Coef.	SE	$P > z$
Constant	0.0354	0.0242	0.143	−0.1142	0.0433	0.008
Age of the household head	0.0092	0.0020	0.000	0.0077	0.0027	0.005
Training received (0/1)	0.2165	0.0724	0.003	0.2237	0.0845	0.008
No education (0/1)	−0.1052	0.0286	0.000	−0.0833	0.0355	0.019
Children under five	0.0254	0.0111	0.022	–	–	–
Remoteness index *Province dummies*	−0.1331	0.0416	0.001	−0.1036	0.0492	0.035
Eastern Highlands (0/1)	−0.1564	0.0454	0.001	0.0102	0.0225	0.650
Western Highlands (0/1)	−0.2195	0.0586	0.000	−0.0023	0.0233	0.922
Simbu (0/1)	−0.0897	0.0344	0.009	0.1019	0.0418	0.015
Jiwaka (reference)	–	–	–	–	–	–
Number of observations	761			730		
Wald chi^2 ($P > \chi^2$)	87.85	*P*-value = 0.000		37.73	*P*-value = 0.000	
Percentage of good predictions	73			78		
Sensitivity	47			23		
Specificity	83			92		
Anderson-Rubin Wald test	0.25	*P*-value = 0.618		2.63	*P*-value = 0.105	
Anderson under-identification test	90.08	*P*-value = 0.000		118.51	*P*-value = 0.000	

methods for estimating the density can be used: the standard kernel density approach; and the sorted data density approach of Lewbel and Schennach (2007). We used the kernel density approach, which is known to be more efficient.[12] We also performed a White's general test for heteroskedasticity in the first step regression of V (the special regressor) on $\boldsymbol{X}$ and $\boldsymbol{Z}$. We reject the null hypothesis of homoskedasticity at the 5 per cent level of significance, which calls for the version of the special regressor estimator that allows for an unknown form of heteroskedasticity in V. Finally, one important assumption of the special regressor method is that -V has the same support as, or larger support than, $\boldsymbol{X}'\beta + \varepsilon$. We test this assumption by comparing the standard deviation and interquantile ranges of V and $\boldsymbol{X}'\beta$ (where β is the vector of estimated coefficients). This assumption is satisfied by our data since the standard deviation of $\boldsymbol{X}'\beta$ is 13, which is comparable in magnitude to the standard deviation of V (11). Also, the difference between the 5th and the 95th quantile of V is 35, comparable to the difference for $\boldsymbol{X}'\beta$ (40).

The Wald tests indicate the global validity of the two models. The percentage of correct predictions is 73 per cent in the model predicting the probability of using PPE and 78 per cent in the model predicting the probability of adopting the least damaging disposal practices. The percentage of correct predictions is higher for negative outcomes (specificity) than for positive outcomes (sensitivity), which is as expected since the

[12] To estimate the density, the Epanechnikov kernel function is used, and the bandwidth is given by Silverman's rule.

proportion of negative outcomes is higher in our sample.[13] The outcomes of the Anderson–Rubin Wald test and Anderson underidentification test confirm the validity of the chosen instrument in the two models. The former indicates a nonrejection of the null hypothesis that the coefficient of the excluded instrument is equal to zero in the model of interest, while the latter confirms that the equation is identified (i.e. that the excluded instrument is correlated with the endogenous regressor). The Sargan–Hansen test of overidentification cannot be performed because the number of instruments is equal to the number of endogenous regressors (one).

Most of the variables are found to be statistically significant and the marginal effects are of comparable magnitude in the two models (except for the province dummies). This finding is not really surprising knowing that the two decisions were found to be statistically dependent. Age is positive and significant in both models thus indicating that safer practices (i.e. wearing some sort of PPE and disposing of chemical containers in the least damaging way) are more likely to be adopted when the household head is older, but its marginal effect is small (around 1 per cent). Older household heads may have a better knowledge of health hazards and/or may be more risk averse. The likelihood of adopting better practices decreases when the household head received no education, which is as expected. Being educated increases the likelihood of wearing some PPE and of burying or burning containers by about 10 per cent. The number of children under five increases the likelihood of using PPE, but the marginal effect is rather small (3 per cent). Again, this is as expected since parents of young children might adopt safer practices in general to protect infants from becoming sick. Our findings show that remoteness has a significant impact on a household's chemical handling practices: an increase from zero to one of the remoteness index implies a 10–13 per cent decrease in the probability of households adopting safe practices. There are significant province effects as far as the use of PPE is concerned, less so regarding the disposal of chemical containers. One possible explanation for the more widespread use of PPE in Jiwaka (used as the reference among the four province dummies) may be the presence, in this particular province, of the oldest and most accessible coffee growing area (known as the Wahgi Valley). Finally, training increases the likelihood of wearing some PPE and of burying or burning containers by around 22 per cent, which is in contrast with findings from Macharia *et al*. (2013) for Kenyan farmers.

For comparison purposes, we estimated the two equations using a bivariate probit model.[14] The marginal effects are found to be of the same sign, but their significance is higher in general in the special regressor model. The percentage of good predictions is slightly higher in the bivariate probit model,

[13] The predicted probabilities are calculated from the estimated index $X'\hat{\beta}$, as suggested by Lewbel *et al*. (2012).

[14] The full set of bivariate probit estimation results are shown in Appendix.

but the special regressor model is found to better predict the positive outcomes. In the model describing the disposal of chemical containers, the bivariate probit model correctly predicts 5 per cent of the positive outcomes, while the special regressor model correctly predicts the positive outcomes in 23 per cent of the cases. The (average) marginal effect of training on the likelihood of wearing some PPE is estimated at 13 per cent in the bivariate probit model and is not statistically significant, while the marginal effect estimated using the special regressor method was 22 per cent. The discrepancy between the estimates obtained using the two approaches casts doubt on the validity of the underlying assumptions of the bivariate probit model. The marginal effect of training on the likelihood of disposing of chemical containers in the least damaging way is estimated at 22 per cent, which is in line with the estimate obtained from the special regressor model.

6. Conclusion

The use of herbicides is widespread among coffee smallholders in PNG, and there is evidence of the mishandling of chemicals by a majority of these farmers. In our sample, 73 per cent of the surveyed farmers did not wear any PPE when mixing and applying herbicides, and 78 per cent disposed of chemical containers in a way that put the community and the environment at risk. Our results show that education and training are important drivers of farmers' pesticide-handling practices. More precisely, we find evidence that being educated and having received training in pest and disease management increases the probability of adopting safer practices by 10 and 22 per cent, respectively. These improved practices contribute to a reduction in farmers' exposure to pesticide-related health hazards as well as a reduced exposure of the entire community to the risk of drinking contaminated water. In the particular case of coffee production in PNG, training was primarily provided by the CIC and by certification companies. Reduced risk exposure and potential improvements in community health (which itself has consequences in terms of farmers' productivity) should thus be accounted for when assessing the benefits of policies promoting sustainable farming practices. Our findings would also suggest that the most remote districts and villages be targeted first. Finally, our article shows that the special regressor approach can be a useful alternative to the more traditional bivariate probit model.

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Appendix

The sample was stratified into 'Treatment households' and 'Control households'. Treatment locations were clusters of villages that were scheduled to be part of the PPAP activities. The process consisted of firstly identifying *lead partners* (coffee export companies, coffee-processing plants, associations and cooperatives) in each of the four provinces. Once the locations where *lead partners* were operating, or committed to operate, were identified in each province, two of the locations were randomly selected. Within each location selected, four villages were randomly selected and, in the same fashion, households were randomly selected from each village (UniQuest Pty Limited, Unpubl. data, 2012). The stratification of treatment location was performed taking into account land characteristics and accessibility to markets. Control locations were selected to match treatment locations in the same areas. These locations had to have similar characteristics to the treatment locations; however, they were not going to receive any assistance from the project and the surveyed households were not aware of the program (UniQuest Pty Limited, Unpubl. data, 2013). In the same way as the treatment locations, a group of villages was first selected and grouped from locations where lead partners were going to operate. Then, villages per location and households within the villages were randomly selected.

Appendix

Table A1 Use of personal protective equipment: bivariate probit estimation results

	Coefficient	SE	Marginal effect	SE
Use of protective equipment				
Constant	0.305	0.241	–	–
Training received (0/1)	0.442	0.471	0.132	0.140
Age of the household head	0.002	0.005	0.001	0.002
No education (0/1)	−0.362***	0.123	−0.108***	0.037
Children under five	−0.187***	0.067	−0.056***	0.020
Remoteness index	−1.137***	0.304	−0.339***	0.089
Eastern Highlands (0/1)	−1.100***	0.182	−0.328***	0.055
Western Highlands (0/1)	−1.390***	0.160	−0.415***	0.048
Simbu (0/1)	−0.543***	0.136	−0.162***	0.041
Jiwaka (reference)	–	–	–	–
Training received				
Constant	−1.678***	0.505	–	–
Age of the household head	0.008	0.011	0.000	0.000
No education (0/1)	−0.477**	0.237	−0.014*	0.008
Children under five	−0.163	0.107	−0.005	0.004
Remoteness index	−6.898***	1.470	−0.203***	0.056
Eastern Highlands (0/1)	−0.104	0.424	−0.003	0.012
Western Highlands (0/1)	−0.182	0.269	−0.005	0.008
Simbu (0/1)	0.343	0.247	0.010	0.008
Jiwaka (reference)	–	–	–	–
Organic coffee predominant (0/1)	6.403***	1.237	0.188***	0.052
Number of observations	761			
Wald chi-square (Prob > chi^2)	228.68	*P*-value = 0.000		
Percentage of good predictions	77			
Sensitivity	43			
Specificity	90			

Notes *, **, *** indicates significance at the 10%, 5% and 1% level, respectively.

Table A2 Disposal of chemical containers (least damaging practices): bivariate probit estimation results

	Coefficient	SE	Marginal effect	SE
Disposal of containers				
Constant	−0.925***	0.108	–	–
Training received (0/1)t	0.971***	0.284	0.266***	0.080
Age of the household head	0.005	0.005	0.001	0.001
No education (0/1)	−0.185	0.123	−0.051	0.034
Remoteness index	−1.048***	0.233	−0.287***	0.064
Eastern Highlands (0/1)	0.198	0.173	0.054	0.047
Western Highlands (0/1)	0.149	0.156	0.041	0.043
Simbu (0/1)	0.846***	0.148	0.232***	0.041
Jiwaka (reference)	–	–	–	–
Training received				
Constant	−1.462***	0.185	–	–
Age of the household head	0.010	0.010	0.000	0.000
No education (0/1)	−0.422*	0.247	−0.014	0.009
Remoteness index	−6.345***	1.436	−0.208***	0.056
Eastern Highlands (0/1)	−0.063	0.424	−0.002	0.013
Western Highlands (0/1)	−0.219	0.274	−0.007	0.009
Simbu (0/1)	0.312	0.255	0.010	0.009
Jiwaka (reference)	–	–	–	–
Organic coffee predominant (0/1)	6.021***	1.207	0.197***	0.052
Number of observations	730			
Wald chi-square (Prob > chi^2)	157.23	*P*-value = 0.000		
Percentage of good predictions	79			
Sensitivity	5			
Specificity	99			

Notes *, **, *** indicates significance at the 10%, 5% and 1% level, respectively.