Bureau d'économie théorique et appliquée (BETA)
UMR 7522

Documents de travail

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Document de Travail n° 2016 – 40

Septembre 2016

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Modeling farmers' decisions on tea varieties in Vietnam: a multinomial logit analysis[§]

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Abstract

This paper analyzes households' choice on tea varieties in Vietnam by using a multinomial logit model. The modelling takes into account the issue of unobserved individual heterogeneity and the endogeneity of some explanatory variables (use of chemical and organic fertilizers). The results show that important factors influencing the decision to adopt one type of tea varieties include income, age, household size, farming contract, and use of organic fertilizers, but also membership of professional associations such as the Tea Association and the Farmers Union.

Keywords: Multinomial logit; Unobserved heterogeneity; Tea varieties; Vietnam

JEL Classification: C25; C12; G12; Q18

[§] Help from colleagues of the economic department of the Vietnam National University of Agriculture in collecting data is gratefully acknowledged. All remaining errors are our own.
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1. Introduction

Recently, studies concerning household behavior have been emphasized, especially in the agricultural sector. Variables that affect farmers' access to information, and hence their perception (e.g., experience, education, individual characteristics, etc.) are typically used in economic models of determinants of adoption (Kebede et al., 1990; Polson and Spencer, 1991; Adesina and Baidu-Forson, 1995; Jayasuriya, 2003; Mafuru et al., 2007; Mpogole and Kadigi, 2012; Kaguongo et al., 2012). Besides, some studies find that the farmers' own characteristics influence their reactions to technological changes and innovations. Such factors include risk-aversion (Ghadim et al., 2005; Feder et al., 1985; Feder and Umali, 1993; Just and Zilberman, 1983) and wealth or household income (Sall et al., 2000). However, while some studies implicitly assume that the technology to be adopted is suitable (Adesina and Baidu-Forson, 1995), it is often difficult to evaluate the advantages or disadvantages of a new technology such as a new crop variety. Choosing a new tea variety can be seen as a technological evolution that delivers utility in terms of both production (e.g., land, labor and yield) and consumption (e.g., quality, prices or market). The decision to adopt one tea variety is not only determined by the farmer's risk attitude but also by the individual preference regarding different product attributes. Even when one tea variety has better production-related attributes, farmers may continue growing the variety that possesses the preferred consumption or market related attributes.

Developing these arguments, this paper seeks to make several contributions to the literature on the adoption of improved crop varieties. Some studies focus on ware potato farmers producing for the market (eg., Abebe et al., 2013; Gildemacher et al., 2011), while some other papers focus on soybean, corn or chickpea (Ojiako et al., 2007; Ouma and De Groote, 2011; Shiyani et al., 2002). Although tea represents an important crop in developing countries, it has received only little attention in the adoption literature, compared to other staple crops such as potato, rice, maize and sorghum. The findings from the existing adoption literature may not be sufficient to understand farmers' decisions regarding tea varieties.

In most cases, probit, logit, tobit or bivariate probit model were applied (see Ayuk, 1997;

Adesina et al., 2000; Nkamleu and Adesina 2000; Adesina and Chianu, 2002; Shiyani et al., 2002; Ojiako et al., 2007; Akinola et al., 2010; Dey et al., 2010; Idrisa et al., 2012). Similarly, some studies also suggested panel data such as Cameron (1999), Conley and Udry (2010) but they said that a lack of panel data has often been a problem in adoption behavior applications. However, to overcome this limit, a few studies suggested to use recall data on each farmer's adoption history as a solution (Besley and Case, 1993; Moser and Barrett, 2006). Adoption decisions can be analyzed using probit or logit models and the farmers' decision is assumed to be of a dichotomous nature.

In addition, other researchers proposed the multinomial logit model (MNL) (see McFadden, 1973; So and Kuhfeld, 1995) and applied it (Bhat and Guo, 2004; Nguyen Van et al., 2004; Dow and Endersby, 2004; Nkamleu and Kielland, 2006; Hassan and Nhemachena, 2008). The advantage of the multinomial logit is that it permits the analysis of decisions across more than two categories, allowing the determination of choice probabilities for different categories. Moreover, previous studies showed that cross-sectional data can be safely used to study adoption decisions when the adoption process moves toward its completion, i.e. when the new technology has already been used for some time (Besley and Case, 1993; Cameron, 1999).

Our study applies the MNL and examines the determinants of the farmers' choice for different tea varieties. The aim of this paper is to provide insights into the determinants of the choice and adoption of tea varieties by analyzing tea producers' assessment in Vietnam.

The remaining of the study is organized as follows. Section 2 discusses the determinants of choice variables, including factors which are related to farmers' choice about tea varieties. Section 3 describes the data we collected ourselves in Vietnam. Section 4 presents the probability model which can be applied to our data. Section 5 reports the estimation results and provides an interpretation for them. Finally, Section 6 concludes the study.

2. Literature review

The literature on the choice model is large enough. In this study, we will emphasize the point as related to agriculture and rural environments. Reviews concerning choice model in agriculture using probabilities can be found in Berkson (1944). Regarding interesting variables, although their effect is expected to be positive or negative in the choice model, the result showed that most of them are discrete dependent variables (Adesina et al., 2000; Adesina and Chianu, 2002; Ojiako et al., 2007; Akinola et al., 2010; Dey et al., 2010; Idrisa et al., 2012). For example, Adesina et al. (2000) used the logit model in their study. Some variables such as gender, farmers' membership in association, contact with extension agencies, village fuel wood scarcity have a positive significance. This result implies that, for instance, male farmers are more likely to adopt than women, etc. In addition, the negatively significant age variable suggested that younger farmers are more likely to adopt improved technologies. The positively significant variable on possession of full rights over trees suggested its positive influence on the likelihood to adopt improved technologies. Finally, the education variable also has a positive effect on the farmer's adoption decisions.

Furthermore, reviews about adoption of improved varieties in agriculture using choice model can be found in many other studies. Shiyani et al. (2002) examined the adoption decision of improved chickpea varieties in farms in Gujarat, India, applying a tobit model. In their study, several variables were significantly influencing the farmers' adoption decisions, such as duration of crop maturity, size of land holding, yield risk, etc. The coefficient of land size holding was found to be negative on the adoption of new chickpea varieties, which means that adoption of new variety is growing faster for small farmers than for large ones. Experience of growing chickpea was significantly positive, suggesting that the farmers with higher experience are more likely to adopt new varieties. The coefficient of yield risk was positive and significant at 10% level. The results also suggest that non-adopters were more risk averse. Further, they considered distance regarding the output market and educational variables but they were not significant. Ojiako et al. (2007) investigated adoption of the improved soybean variety in northern Nigeria, trying to identify the factors influencing the farmers' adoption decisions by applying both logit and tobit models. The results showed that over 60% of the farmers adopted the improved variety. Some factors such as superior yield, grain size, color, resistance to pesticides and diseases were the farmers' reasons for adopting the improved varieties. The adoption of improved soybean technology by farmers is significantly and positively influenced by ecology, yield, expenditure on hired labor, membership in associations and exposure to extension services.

An other interesting study by Asfaw et al. (2011) analyzed the adoption determinants and estimated the effects of adopting improved chickpea technologies on small farms holders in Ethiopia, applying a tobit model. We can observe the effect of some variables such as active family labor force, non-oxen tropical livestock unit per capita, walking distance to the main market, contact with government extension agents, number of improved varieties known in previous years and farmers' perception of improved varieties in their model. They prove to be significant and positive, meaning the level of adoption of improved varieties was strongly related to household wealth indicator variables. Those households with more family labor force, livestock and land were considerably more likely to allocate extra land for the improved chickpea varieties. However, this shows the importance of wealth/poverty level regarding small farms holders' production and their behavior towards technology. Ouma and De Groote (2011) computed the factors affecting adoption of improved corn varieties and fertilizers by farmers in Kenya applying a Heckman model. They used variables such as education, access to credit, hired labor, extension contacts, distance to market, and fertilizers. The results concerning the education variable is significantly positive, revealing its effect on adoption of improved maize varieties. However, it did not show significant as related to adoption of fertilizers. Access to credit and hired labor were positively significant in explaining the adoption decision of improved maize varieties and fertilizers. The number of extension contacts was important in determining the adoption of improved maize varieties but not for the use of fertilizers. Distance to market was negatively associated with adoption of fertilizers, although it was positively associated with the intensity of fertilizer use. The use of fertilizers and improved maize seed was significantly positive at 1% level meaning it is strongly associated with the adoption of improved maize seed and fertilizers. Abebe et al. (2013) considered the adoption of improved potato varieties in Ethiopia. The result indicated that higher education of the household head, gender, access to credit, family size, stew quality of local variety and the presence of a radio and/or television have a significant positive effect on adoption.

3. Data and variables

The data used in this study have been collected through a field survey in three provinces of Vietnam (Tuyen-Quang, Phu-Tho, Thai-Nguyen), conducted by the authors from January to May 2013.[1] It has been carried on randomly from a household lists of ten different villages. It consists of a quantitative survey on 244 tea farmers, based on face to face interviews. Households were asked to provide information on their tea production in 2012. The average duration for the whole questionnaire was 1 hour and 13 minutes with a maximum of 2 hours. Definition of variables is available in Table A1 in Appendix. Summary statistics of variables are reported in Table 1.

Table 1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	Obs.
Tea income	65.67	66.70	2.40	403.0	244
Household size	4.299	1.188	1	10	244
Experience	29.89	13.85	2	64	244
Children	0.217	0.413	0	1	244
Elderly	0.159	0.367	0	1	244
Minority	0.107	0.309	0	1	244
High education	0.328	0.470	0	1	244
Chemical fertilizers	0.732	0.443	0	1	243
Organic fertilizers	0.488	0.501	0	1	242
Contract	0.553	0.498	0	1	244
Youth Union	0.504	0.501	0	1	244
Farmers Union	0.578	0.499	0	1	244
Communist Party	0.204	0.404	0	1	244
Tea Association	0.367	0.483	0	1	218

In this paper, tea incomes are measured in million VND. We observe that the average tea income is about 65.6 million VND per farmer, with a standard deviation of 66.7, and that the

[1] Data and the survey questionnaire are available from the authors upon request.

range of tea income is found between around 2.40 and 403 million VND. These details indicate a large variability in tea income among farmers. In our regressions, we use logarithm of tea income in order to allow some nonlinear effect and to reduce this variability (the distribution of log tea income covers a much smaller range, i.e. between 0.875 and 5.999).

The average number of members in a household is 4.299, with a standard deviation of 1.188 which indicates a large variability in household size in the sample. We think that the household's composition may impact the household choice about tea varieties because their presence in the household can provide an additional labor source, experience transmission, and advice about tea production. To account for these possible effects, we employ two additional explanatory variables which indicate the presence of children and elderly. Farmer's experience can also play an important role. The sample average experience is 29.893 with a standard deviation of 13.855, reflecting a large variability in experience among households.

Our analysis also includes dummies corresponding to households' characteristics such as high education (= 1 if the household's head has a high school degree or above, 0 otherwise) and minority (= 1 if the household belongs to an ethnic minority, 0 otherwise). The data contain 80 households with high education, and 26 households belonging to an ethnic minority group. The purpose of considering these factors is to check whether they can impact the household's varieties choice. Indeed, we might think that a high level of education can favor the access to new technologies of production and to any information that can improve the production. On the contrary, being part of an ethnic minority can involve a lack of advantage compared to the majority groups.

Our data include dummies corresponding to tea production such as the use of chemical fertilizers (= 1 if the household uses chemical fertilizers, 0 otherwise), organic fertilizers (= 1 if the household uses organic fertilizers, 0 otherwise), and contract (= 1 if tea is produced under a farming contract, 0 otherwise). The data contain 118 households using chemical fertilizers, 178 households using organic fertilizers and 135 households with a farming contract. Our analysis also includes dummies such as membership of the Communist Party (= 1 if a member of the household belongs to the Communist Party, 0 otherwise), the Youth

Union (= 1 if a member of the household belongs to the Youth Union, 0 otherwise), the Farmers Union (= 1 if a member of the household belongs to the Farmers Union, 0 otherwise), the Tea Association (= 1 if a member of the household belongs to the Tea Association, 0 otherwise). The data contain 50 households with a member belonging to the Communist Party, 123 households with a member belonging to the Youth Union, 141 households with a member belonging to the Farmers Union and 80 households having a member in the Tea Association.

Table 2: Distribution of tea varieties

Tea variety	Frequency	Percent	Cum.
'Trung-Du'	47	19.34	19.34
'PH1'	32	13.17	32.51
'LDP1'	37	15.23	47.74
'Bat-Tien'	58	23.87	71.60
'Other'	69	28.40	100.00
Black	105	43.21	43.21
Green	138	56.79	100.00

Tea varieties are classified in five categories, 'Trung-Du', 'PH1', 'LDP1', 'Bat-Tien', and the remaining types (category 'Other'). Each of them can be employed to produce green tea and/or black tea. While 'Trung-Du' and 'PH1' correspond to old varieties, other varieties are considered as more recent ones. We note that farmers can cultivate several tea varieties at the same time. The distinction between old and new varieties on the one hand, and between black tea and green tea on the other hand, comes from the recent policy aiming at promoting the tea sector in Vietnam, especially by recommending farmers to increase green tea production and to adopt new tea varieties (cf. Decree 02/2010/ND-CP of the Vietnam Government on agricultural extension enacted in 2010; see also Do Van, 2012).

We thus create a new variable which represents tea varieties from two criteria, old tea versus new tea, on the one hand, and green tea versus black tea, on the other hand. This classification will help us to assess the determinants of the farmers' decision about the adoption of tea varieties. It results in a new classification with multiple choice about tea varieties. There is a total of 6 categories: Old-Black (OB), New-Black (NB), New/Old-Black (NOB), Old-Green (OG), New-Green (NG), and New/Old-Green (NOG).

Table 2 gives the distribution of the data regarding tea varieties. Variety 'Trung-Du' is cultivated by 47 households, namely about 19.34% of the data sample. 'PH1' is cultivated by 32 households (13.17%). 'LDP1' is cultivated by 37 households (15.23%). 'Bat-Tien' is cultivated by 58 households (23.87%) and Other variety is cultivated by 69 households (28.40%). The collected data include 138 green tea producers (56.79% of the data sample) and 105 black tea producers (43.21% of the data sample).

Table 3: Distribution following multiple choice on tea varieties

Tea variety	Frequency	Percent	Cum.
Old-Black (OB)	59	24.28	24.28
New-Black (NB)	18	7.41	31.69
New/Old-Black (NOB)	28	11.52	43.21
Old-Green (OG)	20	8.23	51.44
New-Green (NG)	67	27.57	79.01
New/Old-Green (NOG)	51	20.99	100.00

Table 3 gives the distribution of the data following our classification. The collected data include 18 New-Black observations (7.41% of the data sample), 67 New-Green (27.57%), 59 Old-Black (24.28%), 20 Old-Green (8.23%), 28 New/Old-Black (11.52%), and 51 New/Old-Green tea producers (20.99%).

4. A multinomial logit model for tea varieties

We propose here an econometric model to characterize the farmers' choice about tea varieties among six categories as presented in Table 3.

4.1. Model without farmer's heterogeneity

The general model presented here is based on the works of Nerlove and Press (1973), Greene (2012) and Hausman and McFadden (1984). In our analysis, farmer i makes a choice among six tea varieties: (1) Old-Black (OB), (2) New-Black (NB), (3) New/Old-Black (NOB), (4) Old-Green (OG), (5) New-Green (NG), and (6) New/Old-Green (NOG). Farmer i's utility derived from choice alternative j, $j = 1,...,J$ ($J = 6$) is

$$V_{ij} = X_i'\beta_j + \varepsilon_{ij}, \qquad (1)$$

where the vector of characteristics X_i contains all the factors that influence this utility. The random errors ε_{ij} are assumed to be independent and identically distributed across the J alternatives. Let y_{ij} be the dependent variable with J outcomes numbered from 1 to J. The choice probability is defined by the following multinomial logit framework (after imposing the usual identifying restriction $\beta_1 = 0$):

$$Pr(y_i = 1 \mid X_i) = \frac{1}{1 + \sum_{k=2}^{J} \exp(X_i'\beta_k)} \qquad (2)$$

$$Pr(y_i = j \mid X_i) = \frac{\exp(X_i'\beta_j)}{1 + \sum_{k=2}^{J} \exp(X_i'\beta_k)}, \text{ for } j = 2,...,J. \qquad (3)$$

Estimation of this model is obtained by maximizing the following log-likelihood function

$$\ln L = \prod_i^n \prod_j^J \mathbf{1}(y_i = j) \ln Pr(y_i = j \mid X_i), \qquad (4)$$

where $\mathbf{1}(y_i = j)$ is the indicator function of the household's choice (i.e. it takes 1 if $y_i = j$, 0 otherwise).

4.2. Model with farmers' heterogeneity

To obtain more general specifications, we now allow for the possibility of presence of unobserved individual heterogeneities or individual random effects. The utility of farmer i, $i = 1,...,n$, derived from choice j, $j = 1,...,J$, is given by

$$V_{ij} = X_i'\beta_j + u_i + \varepsilon_{ij}. \qquad (5)$$

The heterogeneity terms u_i are assumed to be mutually independent and independent of X and distributed following a normal density. A similar approach was adopted by Allenby and Lenk (1995), for instance. The probabilities of different choices become:

$$Pr(y_i = 1) = \frac{1}{1 + \sum_{k=2}^{J} \exp(X_i'\beta_k + \sigma_k u_i)} \quad (6)$$

$$Pr(y_i = j) = \frac{\exp(X_i'\beta_j + \sigma_j u_i)}{1 + \sum_{k=2}^{J} \exp(X_i'\beta_k + \sigma_k u_i)}, j = 2,..., J. \quad (7)$$

As the log-likelihood function depends on individual heterogeneities, they have to be integrated out before maximization following the simulated maximum likelihood method (see Stern, 1997). The log-likelihood function becomes

$$\ln L_j = \sum_{i}^{n} \ln\left[\frac{1}{H}\sum_{h=1}^{H}\prod_{j}^{J} Pr(y_i = j \mid X_i, u_i^h)^{\mathbf{1}(y_i = j)}\right],$$

where for each u_i, a number H of pseudo-random draws u_i^h are generated. Based on the discussion of McFadden and Train (2000), we chose $H = 50$ for our simulations.

5. Estimation results

We estimate two different versions of the MNL model in order to analyze the probabilities of the households' choice of tea varieties: a model without unobservable heterogeneity and a model with unobservable heterogeneity. We first compare the models with and without unobservable heterogeneity by using a likelihood ratio test. The computed statistic is $-2(-242.257 + 242.140) = 0.235$, which is much lower than the critical value of a $\chi^2(5) = 11.07$ at the 5% significance level. Hence the model without heterogeneity is not rejected at the 5% level against the model with heterogeneity. Consequently, we solely report the estimation results for the model without unobserved heterogeneity in Table 4. The Wald test is in favor of the model's significance, as the computed value of Wald statistic is $\chi^2(70) = 245.96$ and the corresponding p-value is 0. This implies that the factors used in our analysis can provide a good explanation for farmer's choice about tea varieties.

Moreover, the MNL model is one of the most commonly used regression models for nominal outcomes in economics and social sciences. However, the model has an implicit restriction which consists of the independence of irrelevant alternatives (IIA). Using the approach of Hausman and McFadden (1984) and Cheng and Long (2007), we test the validity of this restriction for our model. Test results show that the IIA cannot be rejected.[2]

Another concern is the endogeneity of some explanatory variables.[3] Indeed, when a farmer makes a decision about tea varieties, his decision about chemical and organic fertilizer uses may be endogenous. For example, some unobserved factors such as production technology and policy variables can determine the type of fertilizer to be used during the production process. Handling this endogeneity issue within a nonlinear framework like our multinomial logit model is not an easy task. Fortunately, Wooldridge (2014) recently proposed a very simple method (named 'variable addition test') to test for endogeneity of explanatory variables in nonlinear models. We follow this method by implementing the following two-step procedure.

1. First, we make a probit regression for each of our two endogenous explanatory variables (use of chemical fertilizers and use of organic fertilizers)

$$Pr(f_{ki}=1)=\Phi(Z'_{ki}\gamma_k)$$

where $k=\{c;o\}$ denotes the type of fertilizer, i.e. c and o meaning for chemical fertilizers and organic fertilizers, respectively. Note that f_k is the binary variable for the use of fertilizer of type k and Z_k is the corresponding instruments set. This step allows us to obtain the generalized residuals (gr) $\hat{g}r_{ki}=f_{ki}\lambda(Z'_{ki}\hat{\gamma}_k)-(1-f_{ki})\lambda(-Z'_{ki}\hat{\gamma}_k)$ where $\lambda(.)$ is the inverse Mills ratio, $\lambda(.)=\phi(.)/\Phi(.)$.

Following Wooldridge (2014), the set of instruments Z_k should strictly encompass all explanatory variables included in the original model (i.e. the multinomial logit regression) and other instruments which are not included in the model (namely excluded instruments). We use the cultivation surface as an excluded instrument.

2. Secondly, we perform the usual multinomial logit regression with two additional

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[2] The test compares the coefficients of a multinomial logit model with 5 alternatives (i.e. one alternative is deleted from the initial set of 6 alternatives) to those of the original multinomial logit model with 6 alternatives. Hence, there is in total five tests to be performed. Under the null hypothesis, the statistic follows a $\chi^2(56)$ distribution. Computed statistics are equal to 0.12, 0.14, 3.07, 2.34, and 8.18 when the alternative 2, 3, 4, 5, or 6 deleted, respectively. All of them are much lower than the critical value of a $\chi^2(56)$ at the 5% level, 31.02.

[3] This issue was pointed out by an anonymous reviewer.

explanatory variables $\hat{gr}_c$ and $\hat{gr}_o$. This allows us to compute a robust Wald test for the null hypothesis that the coefficients of $\hat{gr}_c$ and $\hat{gr}_o$ are jointly zeros. The null hypothesis corresponds to the exogeneity of our two variables of interest (use of chemical fertilizers and use of organic fertilizers). The test is called 'robust' because it is based on robust variance-covariance matrix. In the context of our model, the test statistic corresponds to a $\chi^2(10)$ distribution.

The computed statistic of the test is 12.83 and the corresponding p-value is 0.233, meaning that we cannot reject the null hypothesis. Hence, we can be confident about our analysis which assumes the exogeneity of uses of chemical and organic fertilizers.

It should be noted that coefficients of the model correspond to the effects of explanatory variables on log-odds ratios, $\ln[Pr(y_i = j)/Pr(y_i = 1)]$, for $j = 2,..., J$. They should be interpreted in relative terms, i.e. compared to the first alternative, Old-Black (OB). It is much more convenient to interpret the marginal effects on individual probabilities. The marginal effect of a continuous variable X_l is given by

$$\frac{\partial Pr(y = j)}{\partial X_l} = \left[\beta_{jl} - \sum_{k=2}^{J} \beta_{kl} Pr(y = k) \right] Pr(y = j), \text{ for } j = 1,..., J.$$

This is the formula we employed to compute the marginal effects of log of tea income, household size, and farmer's experience. For the dummy variables, the computation is quite different: the marginal effect is defined by the discrete change in individual probabilities evaluated at the alternative values of the dummy (0 and 1).

Table 5 presents the marginal effects of explanatory variables calculated at the sample means. We remark that there is no relation between the significance of coefficients given in Table 4 and the significance of the marginal effects given in Table 5. In what follows, we discuss the marginal effects.

Table 4: Estimation results for the model without heterogeneity

Variable	NB ($j=2$)	NOB ($j=3$)	OG ($j=4$)	NG ($j=5$)	NOG ($j=6$)
Tea income	-1.360 **	-0.071	-0.480	0.810 **	1.409 **
	(-2.83)	(-0.23)	(-1.16)	(2.66)	(4.20)
Children	-0.762	-0.307	0.280	0.936	0.640
	(-0.77)	(-0.48)	(0.33)	(1.63)	(1.07)
Elderly	1.937 **	0.561	1.820 *	1.169	1.651 **
	(2.06)	(0.73)	(1.76)	(1.57)	(2.07)
Household size	-0.311	-0.099	-0.818 **	-0.001	-0.663 **
	(-1.06)	(-0.46)	(-2.35)	(-0.00)	(-2.61)
Experience	-0.002	0.041 *	-0.043 *	0.005	-0.004
	(-0.05)	(1.76)	(-1.72)	(0.24)	(-0.17)
Minority	1.981 **	-0.095	-1.822	-0.453	-0.152
	(2.01)	(-0.09)	(-0.98)	(-0.41)	(-0.14)
High education	1.205	-0.254	-2.587 **	0.134	-0.979 *
	(1.48)	(-0.42)	(-2.09)	(0.25)	(-1.65)
Tea Association	-0.009	0.929	2.597 **	0.819	1.640 **
	(-0.01)	(1.49)	(2.92)	(1.46)	(2.67)
Farmers Union	1.053	-0.397	0.924	0.689	1.218 *
	(1.22)	(-0.72)	(1.21)	(1.32)	(2.13)
Communist Party	0.090	-0.439	-0.499	-0.712	-1.199 *
	(0.12)	(-0.74)	(-0.55)	(-1.22)	(-1.71)
Youth Union	0.318	-0.320	0.200	1.097 **	1.090 **
	(0.45)	(-0.59)	(0.28)	(2.20)	(2.08)
Contract	1.704 **	0.203	0.661	2.097 **	1.092 *
	(2.06)	(0.35)	(0.83)	(3.77)	(1.87)
Organic fertilizers	2.138 *	-0.294	-1.063	2.457 **	1.239 **
	(2.23)	(-0.48)	(-1.25)	(4.03)	(2.03)
Chemical fertilizers	-0.146	14.16	-2.948 **	-1.105 *	-0.979
	(-0.15)	(0.03)	(-3.59)	(-1.89)	(-1.60)
Intercept	0.602	-14.97	5.355 **	-6.377 **	-4.933 **
	(0.29)	(-0.04)	(2.55)	(-3.78)	(-2.82)

Notes. z-statistics in parentheses. Sample size: $n=216$. * and ** mean for significance at 10% and 5% level, respectively. Likelihood-ratio test for model's significance, $\chi^2(70)=245.96$, $Prob>\chi^2=0$.

Table 5: Marginal effects

Variables	OB ($j=1$)	NB ($j=2$)	NOB ($j=3$)	OG ($j=4$)	NG ($j=5$)	NOG ($j=6$)
Tea income	-0.033	-0.083**	-0.025	-0.042**	0.053*	0.132**
	(-1.18)	(-4.14)	(-1.22)	(-2.43)	(1.91)	(4.80)
Children	-0.031	-0.053	-0.047	0.003	0.103*	0.025
	(-0.47)	(-1.11)	(-0.90)	(0.07)	(1.70)	(0.46)
Elderly	-0.186**	0.059	-0.019	0.049	0.009	0.087
	(-2.11)	(1.50)	(-0.33)	(1.13)	(0.13)	(1.32)
Household size	0.044*	-0.008	0.008	-0.031**	0.052*	-0.066**
	(1.92)	(-0.61)	(0.47)	(-1.98)	(2.27)	(-2.69)
Experience	-0.001	-0.003	0.004**	-0.002**	0.001	-0.001
	(-0.52)	(-0.23)	(2.06)	(-2.10)	(0.31)	(-0.42)
Minority	0.024	0.113**	-0.006	-0.091	-0.063	0.022
	(0.21)	(2.72)	(-0.07)	(-1.02)	(-0.55)	(0.22)
High education	0.060	0.075**	-0.006	-0.121**	0.086	-0.095*
	(0.96)	(2.09)	(-0.13)	(-2.07)	(1.56)	(-1.71)
Tea Association	-0.170**	-0.038	0.032	0.096**	-0.023	0.101*
	(-2.63)	(-1.11)	(0.68)	(2.45)	(-0.43)	(1.93)
Farmers Union	-0.078	0.036	-0.080*	0.023	0.005	0.093*
	(-1.40)	(0.91)	(-1.76)	(0.67)	(0.09)	(1.74)
Communist Party	0.088	0.026	-0.009	-0.002	-0.016	-0.087
	(1.34)	(0.77)	(-0.18)	(-0.04)	(-0.25)	(-1.27)
Youth Union	-0.068	-0.003	-0.067	-0.012	0.084	0.065
	(-1.24)	(-0.09)	(-1.48)	(-0.38)	(1.61)	(1.35)
Contract	-0.162**	0.045	-0.050	-0.007	0.188**	-0.013
	(-2.80)	(1.26)	(-1.09)	(-0.21)	(3.44)	(-0.25)
Organic fertilizers	-0.134**	0.071*	-0.097**	-0.096**	0.246**	0.008
	(-2.31)	(1.70)	(-2.06)	(-2.68)	(4.01)	(0.16)
Chemical fertilizers	-0.604	-0.116	1.492	-0.216	-0.317	-0.247
	(-0.01)	(-0.01)	(0.02)	(-0.04)	(-0.02)	(-0.02)

Notes. z-statistics in parentheses. Sample size: $n = 216$. * and ** mean for significance at 10% and 5% level, respectively.

Log of tea income has a significantly negative influence on the New-Black choice ($j = 2$) and the Old-Green choice ($j = 2$). Moreover, tea income has a significantly positive effect on both New-Green choice ($j = 5$) and New/Old-Green choice ($j = 6$) at the 5% significance level, respectively. This result is in line with the study of Udensi et al. (2011). It appears that an increase in tea income is associated with the adoption of new green tea varieties.

Our estimation results also suggest that the presence of elderly members in the household has a significantly negative effect on the probability of adopting Old-Black tea ($j = 1$). This could be explained by the fact that older people are unlikely to favor the old technology. This result is consistent with the study of Timu et al. (2014). In addition, the children variable has a positive impact on the household's choice about the New-Green variety. While Nkamleu and Kielland (2006) noticed how children are kept out of cocoa farming, the presence of children in the household constitutes a favorable factor to adopt new green tea regarding our data.

The effect of households size is relatively complex. It is negative for the probability of Old-Green ($j = 4$) and New/Old-Green ($j = 6$) whereas it is positive for the probability of adopting Old-Black and New-Green variety. This contradictory result was also obtained by some existing studies (Gebremedhin et al., 2009, Asfaw et al., 2011, Abebe et al., 2013, and Timu et al., 2014).

Regarding variables that characterize the head of household (experience, ethnic minority, and high education), experience has a positive effect on New/Old-Black choice and negative effect on Old-Green choice. Hence, the farmer's experience increases the adoption of black tea (both new and old varieties) but diminishes the chance of green tea production from old varieties. Ethnic minorities have a preference for New-Black tea ($j = 2$). Highly educated farmers also prefer this choice ($j = 2$) but are unlikely to adopt green tea production ($j = 4$ and $j = 6$). This result is not contradictory with the existing results. Indeed, Clay et al (1998) found that education was an insignificant determinant of adoption decisions, while other studies found that education was negatively correlated with such decisions (Gould et al., 1989; Okoye, 1998; Adesina et al., 2000; Hassan and Nhemachena, 2008; Gebremedhin et al., 2009; Ouma and De Groote, 2011; Abebe et al., 2013; Adisa et al., 2013). Shiyani et al. (2002) also found that the effect of education level is not significant.

Now considering membership of political and professional groups, membership of the Communist Party and the Youth Union has no significant effect on farmer's choice about tea varieties. However, belonging to the Tea Association and the Farmers Union has an interesting impact. Indeed, the Tea Association variable has a significantly negative effect on Old-Black choice ($j=1$) and a positive effect on Old-Green choice ($j=4$) and New/Old-Green choice ($j=6$), consistently with the results of Adesina et al. (2000) and Ojiako et al. (2007). Furthermore, the Farmers Union variable has a negative effect on New/Old-Black choice ($j=3$) and a positive effect on adopting New/Old-Green ($j=6$), similarly to the results of Atta-Krah and Francis (1987), and Versteeg and Koudokpon (1993). Our results show that the professional network (Tea Association, Farmers Union) is clearly in favor of green tea production, regardless of whether it corresponds to an old or new variety.

Regarding the farming contract variable, it has a significantly negative impact on Old-Black ($j=1$) and a positive impact on New-Green ($j=5$), indicating that farmers having a contract with a company are more receptive to adopt new technology, in particular to produce green tea from new varieties.

Finally, concerning fertilizer variables, use of chemical fertilizers has no significant impact on any choice probability. Use of organic fertilizers is positively and significantly related to choices New-Black ($j=2$) and New-Green ($j=5$), whereas it is negatively associated with Old-Black, New/Old-Black ($j=3$), and Old-Green ($j=4$). This implies that using organic fertilizers determines the adoption of new varieties to produce either green tea or black tea. Similar results can be found in Ouma and De Groote (2011) and Owusu et al. (2013).

6. Conclusions

The main aim of our study is to provide insights into the determinants of the choice of tea varieties by farmers in Vietnam, focusing on the role of farmers' characteristics and other external factors. Our measure of farmers' decisions is the extent of adoption of tea varieties based on a multinomial choice model.

Our analysis accounts for two variants of the multinomial logit model (with and without unobserved individual heterogeneity) and endogeneity of some explanatory variables (uses of fertilizers). Our preferred model corresponds to the linear index model without unobserved heterogeneity where all explanatory variables are exogenous. The results reveal that important factors which influence the adoption of tea varieties include tea income, presence of elderly and children in the household, use of organic fertilizers, contract farming, and membership of Tea Association and Farmers Union. These variables correspond to the factors to which one should pay attention in order to favor the adoption of a certain type of tea varieties.

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Appendix

Table A1: Definition of variables

Variable name	Definition	Nature
Tea income	log of income from tea production (in VND)	continuous
Experience	year of experience of the household's head	continuous
Household size	number of members in the household	continuous
Tea varieties		
'Trung-Du'	name of old tea variety	dummy
'PH1'	name of old tea variety	dummy
'LDP1'	name of new tea variety	dummy
'Bat-Tien'	name of new tea variety	dummy
'Other'	remaining varieties	dummy
Organic fertilizers	use of organic fertilizers	dummy
Chemical fertilizers	use of chemical fertilizers	dummy
Contract	household has a farming contract with a company	dummy
High education	high educ. level of the household's head (high school or above)	dummy
Minority	being part of a minority ethnic group	dummy
Children	presence of members less than 18 years old	dummy
Elderly	presence of members more than 60 years old	dummy
Tea Association	one of the household's members belongs to this association	dummy
Farmers Union	one of the household's members belongs to this association	dummy
Youth Union	one of the household's members belongs to this association	dummy
Communist Party	one of the household's members belongs to this association	dummy