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Auteurs

Nicolas Lampach, Phu Nguyen-Van, Nguyen To-The

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Bureau d'Économie Théorique et Appliquée
BETA - UMR 7522 du CNRS

BETA Université de Strasbourg
Faculté des sciences économiques et de gestion
61 avenue de la Forêt Noire
67085 Strasbourg Cedex
Tél. : +33 (0)3 68 85 20 69
Fax : +33 (0)3 68 85 20 70
Secrétariat : Géraldine Del Fabbro
g.delfabbro@unistra.fr

BETA Université de Lorraine
Faculté de droit, sciences économiques
et de gestion
13 place Carnot C.O. 70026
54035 Nancy Cedex
Tél. : +33(0)3 72 74 20 70
Fax : +33 (0)3 72 74 20 71
Secrétariat : Sylviane Untereiner
sylviane.untereiner@univ-lorraine.fr

http://www.beta-umr7522.fr

Determinants of the Adoption of Organic Tea Production in Northern Vietnam: A Robustness Analysis[§]

Nicolas Lampach[a*] Phu Nguyen-Van[b]

Nguyen To-The[c]

[a] *Centre for Legal Theory and Empirical Jurisprudence, KU Leuven*

[b] *BETA, CNRS & University of Strasbourg, France*

[c] *Vietnam National University of Agriculture, Vietnam*

Abstract

Increasing consumer awareness on sustainable and healthy food choices gave rise to a growing demand for organic tea in the past decades. Most of this demand is met by imports from developing countries. This article examines the main factors affecting the choice of farm households to adopt organic tea production in Northern Vietnam. We apply a logit model to survey data on 241 Vietnamese tea farming households. We assess the robustness of the results by addressing three important statistical issues: (*i*) regressor endogeneity, (*ii*) unobserved heterogeneity at farm level and (*iii*) missing values. The main results are chiefly robust and largely in line with the theoretical predictions. We find that farm households with higher revenues and located in rich natural and physical environments are significantly more inclined to adopt organic tea production. Furthermore, the analysis reveals that farm households being consulted by extension agents and belonging to a tea association increase the odds for the adoption of organic tea cultivation.

Keywords: Organic farming; Regressor endogeneity; Unobserved heterogeneity; Multiple imputations method; Tea production; Vietnam

JEL Classification: Q15; O33; Q18

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[*] Corresponding author: *Address*: International House, 45 Tiensestraat, 3000 Leuven; *E-mail:* `nicolas.lampach@kuleuven.be`, *Tel:* +32 16 37 76 08

1 Introduction

Increasing consumer awareness of food safety and quality have spurred the expansion of international trade in high-value food products over the last decades. Policymakers have recognized the potential of organic farming as a measure to ensure sustainability and meet the mounting demand of high quality food products. Organic farming[1] has received ample attention in most of countries where food safety problems and gaps in the supply of organic products are at stake. Since 1980, the development of organic farming–which prohibits the use of any synthetic agrochemicals–was mainly driven by committed farmers and consumers in the United States and Europe. Organic production has increased in developing countries due to the high demand of organic products in developed countries. Despite the positive trend, the overall rate of conversion to organic farming in developing countries has been observed to increase much slower than expected.

Tea counts as the manufactured beverage most consumed in the world and represents an important commodity in terms of labor and income for a large number of developing countries (FAO, 2015). In Vietnam, tea is one of the primarily export crops and the country is ranked as one of the top ten countries in the world in terms of tea production and exports (Tran, 2009). Vietnamese tea production is predicted to increase from 115.696 tonnes in 2011 to 148.101 tonnes in 2021, reflecting an annual average growth rate of 2.5 percent (FAO, 2012). In contrast, Vietnam is facing difficulties in fostering trade marks, improving the low tea quality and complying with food safety standards. The currently poor quality and low level of product safety of Vietnamese tea are mainly attributable to monoculture farming and the misuse of chemicals (fertilizers and pesticides).

In August 2005, the Vietnamese Tea Association (VTA) recommended a package of measures to improve the quality of tea. The Ministry of Agriculture and Rural

[1] There exist many definitions of organic farming. A more general form can be found in the Codex Alimentarius Commission created in 1963 by the Food and Agriculture Organization of the United Nations (FAO) and the World Health Organization (WHO) referring to "*organic farming involves holistic production management systems (crops and livestock) emphasizing the use of management practices in preference to the use of off farm inputs*".

Development in Vietnam is encouraging a shift to organic farming by setting organic tea production as a key priority into Vietnam's National Policy Framework. The organic market in Vietnam is very small and there exist solely a limited number of Vietnamese tea products certified as organic. Nowadays, a growing number of land of tea production is converted to organic farming in Vietnam (Tran, 2009). In 2001, only 2 hectares of organic land were managed by 38 farms in Vietnam representing 0.003 percent of total agricultural area. In 2015 the certified organic area was 37490 hectares representing 0.36 percent of the total agricultural area of Vietnam (Hsieh, 2005; Willer and Kichler, 2015). Furthermore, a switch from conventional to organic production might be beneficial for both producers and the society as it reduces the health and environmental impacts of pesticide usage. Providing a better understanding about the determinants affecting the adoption of organic farming practices might be considerably important for the Vietnamese agricultural policy to establish effective measures and foster the exports of high-value food products.

Agricultural economics primarily utilizes cross-sectional data where observations are independent of each other. The bias associated with endogeneity has received widespread attention from scholars in recent years, but surprisingly little attention has been given to other statistical problems caused by unobserved heterogeneity and the occurrence of missing values in survey data. In particular, the presence of unobserved heterogeneity and missing values can lead to inefficient estimation and can give inconsistent results. Thus, it becomes necessary to undertake a rigorous robustness analysis to draw credible inference from the estimated results.

This study aims to determine the main characteristics influencing the adoption of organic farming in the Vietnamese tea sector. We use cross-section data of 241 tea farming households collected by our own through a survey questionnaire in 2013. Logit model estimation is used to analyze the relationship between the key determinants and the adoption of organic tea production at farm-household level. The robustness of the results are assessed under three statistical angles: (*i*) regressor endogeneity, (*ii*) unobserved heterogeneity at farm level and (*iii*) missing data from the survey.

In the agricultural adoption literature, extensive studies have found significant effects of gender, education, concern for the environment, trust in government and market, and information services on the adoption of alternative agricultural practices, likewise traditional, organic or agro-forestry systems (Haugen and Brandth, 1994; Burton et al., 2003; Fairweather and Campbell, 2003; Darnhofer et al., 2005; Flaten et al., 2005; Koesling et al., 2008; Läpple, 2010; Karki et al., 2012; Baumgart-Getz et al., 2012; Läpple and Kelley, 2015). Of utmost interest are also the articles by Jansen (2000) and Padel (2001) reviewing a large number of studies of organic farming related to the adoption model. Scholars primary apply non-linear models to estimate the main factors of the adoption of alternative agricultural practices where the dependent variable is dichotomous[2].

This article makes a contribution to the extensive adoption literature in the field of organic farming by focusing on a novel survey database and providing support for policy actions by promoting organic farming. Secondly, this article contributes to the methodology literature by assessing more rigorously the robustness of the results while considering three alternative specifications in the empirical analysis.

The remaining of this article is organized as follows. Section 2 introduces the conceptual framework and the hypotheses deduced from the theoretical model. Section 3 presents the data used in the analysis. Section 4 introduces the empirical framework and outlines the main findings. Section 5 discusses four different alternative specifications to deliver robust results. Section 6 concludes and gives an outlook on the Vietnamese agricultural policy and organic tea sector.

2 Theory

Rogers (1962, p.21) explains that "*the adoption decision occurs when an individual (i.e decision maker) engages in activities that lead to a choice to adopt or reject the innovation*". The theoretical developments on the adoption of agricultural innovations are generally based on decision making theory illustrating that farmers decide whether

[2]We acknowledge that a continuous variable–share of land under the new crop or the duration of the adoption–indicating to what extent a new crop is adopted might be more informative. Unfortunately, we neither have accurate indicators about the percentage of land cultivated by organic farming nor the duration of the adoption in our database.

to choose between a traditional or modern technology by maximizing their expected utility (Feder et al., 1985).

Our hypotheses are deduced from the stochastic production model developed by Hiebert (1974) on the adoption behavior of farmers. The model aims on the effect of uncertainty and imperfect information on fertilizer use and allocation of land to new modern technology. In his approach farmers have not perfectly known information about the characteristics of new and improved inputs. This implies a greater exposure to risks as there are uncertainties in production and the possibility that farmers make allocative errors. In Hiebert's model, farmers may gain more information about the new technology to reduce the risks associated with allocative errors and uncertainties in production. As a result, the probability of adopting the new modern technology increases.

We ascertain that the new modern production[3] requires a modern input[4], e.g organic fertilizer and land. For instance, we suppose that yield response to fertilizer has increased, however the farmer (or farm household head) is unsure about the specific change in response. According to Hiebert (1974), the output of modern production is a function of fertilizer input N, fixed parameter α which is subjectively random in the Bayesian sense, land Z and the state of nature β. Thus, the production function can be written as:

$$y_M = f_M(N(\alpha), Z, \beta) \tag{1}$$

f_M is assumed to be strictly concave ($f'_M < 0$ and $f''_M > 0$). The farmer can chose how much land is allocated to the modern production. The remaining land is allocated to the traditional old production. Hiebert (1974) supposes that the traditional cultivation is realized without fertilizer and the output of both production systems is homogeneous. Hence, the total output obtained by the farmer is given by:

$$y = f_M(N(\alpha), Z, \beta) + f_T(\overline{Z} - Z, \beta) \tag{2}$$

[3] Hiebert (1974) considers the adoption of high yielding seed varieties. In this article modern production can be associated with organic farming.

[4] For the sake of simplicity, no other input variables are considered.

where f_T is assumed to be strictly concave, Z is the land allocated to the modern production and $\overline{Z}$ is the total available land. The superscript M and T denote modern and traditional production, respectively. Furthermore, Hiebert (1974) assumes that α and β are distributed independently of the input levels. However, we suppose that larger values of the random variables yield higher outputs from both production methods[5]. Considering a certain commodity price p and the price of fertilizer c, the farmer maximizes the expected net income which follows as:

$$E[U(\pi)] = E[U(pf_M(N(\alpha), Z, \beta) + pf_T(\overline{Z} - Z, \beta) - cN)] \tag{3}$$

Solving equation (3) with respect to the input levels, N and Z while assuming risk aversion[6] leads to the following intuition of the results. Risk averse (loving) farmers will use less (more) land and less (more) fertilizer in modern production than a risk neutral farmers. This means that farmers are reluctant to the variance of net income and chooses lower input levels. We hypothesize that more wealthy farm households may also be able and willing to bear more risks than poor farm households and thus farm household's with higher revenues will be more likely to adopt organic farming. It has been reported in the literature that farm households with higher incomes are more likely to adopt innovations compared to those with lower incomes due either to having a positive perception for marketability of the modern crop or greater financial feasibility for investing in new technologies (Negatu and Parikh, 1999, Dey et al., 2010, Udensi et al., 2011).

- *Hypothesis 1: Farm households with larger revenues are more likely to adopt organic tea production*

Now, we consider the case where the farmer gains additional information about the unknown parameters of the production function. The farmer must acquire new information concerning the efficient handling of appropriate practices to control pests and diseases. According to Hiebert (1974) the probability of receiving net income from modern production is greater than π_M and increases as learning occurs. Furthermore,

[5] It is plausible to argue that rainfall increases output under both production methods.

[6] Farmer's utility function is assumed to be strictly concave $U' < 0$ and $U'' > 0$

we consider that the distribution function F_M after acquiring additional information stochastically dominates the distribution function F_T given the original stock of information. Two crucial points can be deduced from this theoretical results. Firstly, farm household may acquire new information about innovative applications from extension agents or through farm associations. The literature points to the fact that associations enhance the interaction among farmers (Versteeg and Koudokpon, 1993; Ojiako et al., 2007; Owusu et al., 2013; Adebayo and Oladele, 2013 and Abdoulaye et al., 2014). For this reason, we postulate that farm households belonging to a tea association are more likely to adopt organic tea production compared to those which are not being part of it.

- *Hypothesis 2: Farm households being part of a tea association are more likely to adopt organic tea production*

In line with the literature, we assert that farmers who have not been consulted by extension agents have a lower probability to adopt organic farming than those of being consulted (Adesina and Zinnah, 1993; Shiferaw and Holden, 1998; Chirwa, 2005; Akinola et al., 2010; Ali and Abdulai, 2010; Owusu et al., 2013; Abdoulaye et al., 2014).

- *Hypothesis 3: Farm households who have been consulted by extension agents are more likely to adopt organic tea production*

The probability of adopting a new modern technology may also depend on the natural and physical environment of cultivation ((Nelson and Phelps, 1966; Welch, 1970; Hiebert, 1974). Higher soil quality, better water availability and efficient irrigation systems increases the expected utility of net income from modern production and thus increases the likelihood of adopting the new technology. We postulate that farms which are located in more favorable environment will be more likely to adopt organic tea production.

- *Hypothesis 4: Farm households located in a rich natural and physical environment are more likely to adopt organic tea production*

While setting up this four testable hypotheses, we explain the data and variables used for the empirical analysis in the following section.

3 Data and variables

A survey[7] was carried out from January to May 2013 by our team in three provinces located in Northern-Vietnam, namely Tuyen-Quang, Phu-Tho and Thai-Nguyen (See Figure 1).

− − −[Figure 1 here] − −−

Participants were randomly selected from a farm households list of ten villages. We asked the participants to provide information about their tea production of the previous year. Additionally, we organized face to face interviews with the household head. The average duration of the questionnaire lasts 1 hour and 13 minutes with a maximum of 2 hours. Quantitative and qualitative information have been collected for a total sample of 241 Vietnamese farm households.

Tea cultivation in Vietnam is mostly concentrated in the three provinces of the study and the Central Highlands representing about approximately 60% and 20% respectively of total area in 2009 according to the Vietnamese tea association. Although our sample contains only 241 farmers which can be viewed as a moderate sample size. It results from a randomly sampling procedure, which gives comparable figures compared to the values related to the total Vietnamese tea sector reported by the General Statistical Office (GSO). According to GSO (2011), the productivity of the Vietnamese tea constitutes about 5-18 tons/ha during the period 1961-2011 whereas our sample presents an average productivity of 6.72 tons/ha and a standard deviation of 5.75 tons/ha (the distribution range is comprised between 0.10 and 23.33 tons/ha). While our sample is not nationally representative, we allege that the results are applicable to the tea production in Northern Vietnam.

[7]Note that local enumerators conduct the survey. They were prior trained by staff members while receiving general instructions and exercises.

A summary of the data and variables used in the empirical analysis are presented in Table 1. Recall that the dependent variable is CHOICE, a binary variable indicating whether the farm household adopts organic tea cultivation. More precisely, this variable equals 1 if the farm opts to produce organic tea otherwise equals 0 (the farm produces conventional tea). The set of explanatory variables includes REVENUE, LAND, EXPERIENCE, HHSIZE, HEDUC, MINORITY, GENDER, TASSO, EXTENSION, and province dummies (for provinces Tuyen-Quang, Phu-Tho, and Thai-Nguyen, the last dummy being the reference). Except for descriptive statistics reported in Table 1, which correspond to the levels of household's income, land area, and labor, in the estimations we use the logarithm values of REVENUE, LAND, and LABOR to reduce the heterogeneity and presence of possible outliers in the data.

$$- - -\left[\text{Table 1 here}\right] - - -$$

The variable REVENUE is measured in million VND (21,148 VND is equivalent to 1$ indicated by the World Bank). The average tea revenue is about 65.7 million VND (3.106 USD) per farmer, with a standard deviation of 67.1 million VND (3.173 USD). One could object that the variable revenue might not be appropriate to use in the model. But as we do not have any other source of data for these groups of farmers, we were left with no other choice. Instruments for revenue were not available to remove the endogenous problem of farm revenue per cultivated land area (Zeller et al., 1998; Negatu and Parikh, 1999; Adesina and Chianu, 2002; Dey et al., 2010 and Udensi et al., 2011).

The variable LAND represents the total farm size of the farm household in hectares. The average farm land is about 0.58 hectares per household. As presented in the summary statistics the variable presents a high variability. For this reason, we use the variable in logarithm form to reduce the variability in the subsequent estimation.

The average experience of farmers is 29.7 years with a standard deviation of 13.8. The duration of farmer's experience may effect positively or negatively the adoption choice. Young farmers have been found to be more knowledgeable about new practices, more willing to bear risk and more likely to adopt new practices (technologies) due to longer planning horizons. Old farmers are less likely to adopt new practices as they feel confident in cultivating tea in their old ways and methods. On the other hand, old farmers may have more experience, resources, or authority that may endow them with more capabilities to adopt new practices (Nguyen Van et al., 2004; Abebe et al., 2013; Abdoulaye et al., 2014).

The average number of household size is 4.3 household members, with a standard deviation of 1.2. In the adoption literature, the variable household size has been identified to affect either positively or negatively the decision to adopt a new modern technology (Kebede et al., 1990; Shiferaw and Holden, 1998;Zeller et al., 1998; Staal et al., 2002; Udensi et al., 2011; Kafle and Shah, 2012; Abdoulaye et al., 2014).

We include dummies corresponding to household characteristics, likewise higher education, minority, gender, tea association (TASSO) and extension (EXTENSION). In our data, 80 households have a higher education, 26 households are belonging to a minority ethnic group, 79 households are member of a tea association and 173 households have been contacted by extension agents.

HEDUC is a proxy for the head of the farm household's higher educational level and is measured as a dummy variable which takes the value one if the farmer reported to have benefited from formal school education and zero otherwise. Studies have shown that farmers with higher education tend to be more likely to adopt new innovations (Padel, 2001; Storstad and Bjørkhaug, 2003; Ouma and De Groote, 2011; Kafle and Shah, 2012; Abebe et al., 2013; Abdoulaye et al., 2014). GENDER is a dummy variable and equals one if the head of the household is a male and zero otherwise. Scholars argue that women are generally discriminated in terms of access to external inputs and are less likely to adopt the new modern technology (Haugen and Brandth, 1994; Adesina, 1996; Jansen, 2000 and Abdoulaye et al., 2014).

A large majority of farm households (57%) are located in the mountainous midland province Thai-Nguyen which constitutes one of the largest tea producing area in Vietnam. The climate conditions (temperature and rainfall) make the province favorable for agricultural development. Field land represents 12.4% of the total land area and a part of it is exposed to droughts and floods which make harvesting more difficult. Another 30% of farm households are situated in the province Tuyen-Quang and a minority (13%) is located in the province Phu-Tho. The latter represents one of the poorest areas of Vietnam and households depend largely on tea cultivation. In the last few years, French development aid programs financed new plantations in the province of Pho-Tho between 2001 and 2004 to enhance the economic development of rural population and improve their living conditions (French development agency, 2004).

4 Estimation results

To analyze the adoption of organic tea production, we employ the following logit model (see Amemiya, 1981 and Maddala, 1991):

$$y_i^* = x_i \beta + \varepsilon_i, \tag{4}$$

where y_i^* is a latent variable which represents the net utility corresponding to organic tea production compared to traditional (or conventional) tea production. We observe the decision of tea producer i, which is a binary variable, i.e. $y_i = 1$ if producer i adopts organic tea production and $y_i = 0$ if (s)he selects the traditional production. This corresponds to variable CHOICE in the data. The adoption decision depends on producer's characteristics and other control variables, represented by x_i, and an unobserved random factor ε_i. We adopt the logit specification with the following probability

$$Pr(y_i = 1 \mid x_i) = \frac{\exp(x_i' \beta)}{1 + \exp(x_i' \beta)}, \tag{5}$$

and the corresponding log-likelihood function

$$\ln L_i = \sum_{i=1}^{n} \left\{ \mathbf{1}(y_i = 1)\ \ln Pr(y_i = 1 \mid x_i) + \mathbf{1}(y_i = 0) \ln \left[1 - Pr(y_i = 1 \mid x_i)\right] \right\}, \tag{6}$$

where $\mathbf{1}(.)$ is the indicator function of producer's choice.

Table 2 reports estimation results (coefficients and marginal effects) of the logit model concerning the choice of organic tea production.[8] Estimation results for the logit model show that farm households having higher revenues, belonging to a tea association, being consulted by extension agents and located in the Phu-Tho province are significantly more likely to adopt organic tea cultivation.

In particular, for each additional unit of revenue (in log), the farm is 8.8% more likely to produce organic tea in comparison with those that cultivate conventional tea. This result corroborates with *hypothesis 1* and is consistent with the findings of Negatu and Parikh (1999), Dey et al. (2010) and Udensi et al. (2011). Economic factors play an important role in the adoption decision of new technologies (Adesina and Chianu, 2002). It is argued that wealthier farm households tend to behave more risk seeking and might have additional financial resources available to compensate potential losses. Our proxy variable LN REVENUE includes partly the information of the tea price. One could object in terms of estimation that the proxy revenue as an exogenous variable might not be appropriate and that a reverse effect can exist as the choice of organic farming may have an impact on the household's income. The next section will be devoted to the possible endogeneity of LN REVENUE as well as EXTENSION (contact with extension agents).

$$- - - \Big[\text{Table 2 here}\Big] - - -$$

Several authors have used recursive econometric models to explain the adoption of agricultural technology and related income effects (Zeller et al., 1998). A similar framework is applied in this article. We define the adoption of organic tea and the resulting revenue generation as a sequential decision making process whereby previous cropping decisions predetermine farm revenue. A tea association member is significant and 25.2% more likely to produce organic tea than non-member. This result is

[8] It is well known that the marginal effect of explanatory variable x_k on adoption probability is given by $\partial p/\partial x_k = p(1-p)\beta_k$ with $p \equiv Pr(y_i = 1 \mid x_i)$. Note that the marginal effect of a continuous explanatory variable represents changes in the dependent variable when the explanatory variable increases by one unit. The marginal effect of a categorical explanatory variable is differently computed, i.e. it corresponds to changes in the dependent variable when the latter shifts from zero to one.

consistent with *hypothesis 2* and in line with the literature revealing a positive relationship between the membership of a tea association and the adoption of organic tea cultivation. Farmers who are part of a tea association were more likely to adopt the production of organic tea (Saka et al., 2005; Owusu et al., 2013 and Adebayo and Oladele, 2013). Agricultural development agencies have high rates of success when they work with farmers' groups or associations (Versteeg and Koudokpon, 1993).

Farm households consulted by extension agents are significantly and 7.3% more likely to produce organic tea than those not being consulted. In line with *hypothesis 3*, the extension activities reflect the efficiency of the agricultural extension system in recent times. This finding is to some extent in line with the results of Adesina and Zinnah (1993), Ojiako et al. (2007), Ali and Abdulai (2010), Owusu et al. (2013) and Abdoulaye et al. (2014). Meanwhile, Adebayo and Oladele (2013) also show that farmers who have been contacted by extension agents are less likely to practice organic farming techniques. This variable can be potentially endogenous because of a reverse effect: the adoption of organic tea production can lead to a more frequent contact with extension agents as farmers would feel the need for more information in this case than the traditional/conventional tea. We will address the endogeneity of this variable in the next section.

In line with *hypothesis 4*, our estimation results demonstrate that farm households situated in the province Phu-Tho are significantly and 36.1% more likely to cultivate organic tea compared to farm households located in Thai-Nguyen (which serves as the reference category). The marginal effect of the province Phu-Tho is of substantially large size and might be influenced by other relevant factors.[9] In the last years, several initiatives were given rise to the production of organic products in the province Phu-Tho. For instance, a seven-year organic farming product during 2005-2012 has been launched by the Danish Government in assistance with Vietnam Farmer Union. The main objective of the project aims on increasing awareness and knowledge on organic farming and providing assistance in the production and marketing of the products

[9] We acknowledge that we are not able to disentangle the effect of climate conditions and soil from other factors, likewise road rehabilitation, transport access, development program aid, local market or industrial parks.

(Dam, 2016).

Several authors mentioned that both education and experience play a significant role in the adoption decision (Kebede et al., 1990; Strauss et al., 1991; Ayuk, 1997; Adesina and Chianu, 2002; Saka et al., 2005; Langyintuo and Mungoma, 2008; Ouma and De Groote, 2011; Kafle and Shah, 2012; Abebe et al., 2013; Abdoulaye et al., 2014 and Schultz, 1975). However, these variables were not found to be significant in our estimation. Furthermore, the variable gender has been considered to be important but we could not find any significant effect in our model.

5 Robustness analysis

Different alternative specifications and data treatments can be employed to deliver robust results. We will consider four possible issues. The first one is the inclusion of unobserved heterogeneity into the choice model as we think that farmer's decision can be linked to some motivation and characteristics that econometricians are not able to observe. This problem can give inefficient estimation (i.e. the estimator does not have the smallest variance). The second case deals with the problem of endogenous regressors that can bias estimation results. The third issue is related to missing values from survey as it can alter the quality of the regressions (i.e. the estimator might be inconsistent). Finally, the last issue is the goodness-of-fit of the selected model.

5.1 Farmer's unobserved heterogeneity

To obtain a more general specification, we allow for the presence of a random effect (or producer's unobserved heterogeneity). In this case, the probability of adopting organic tea production becomes

$$Pr(y_i = 1 \mid x_i, \mu_i) = \frac{\exp(x_i'\beta + \sigma\mu_i)}{1 + \exp(x_i'\beta + \sigma\mu_i)}, \tag{7}$$

and the probability of choosing the conventional tea production is similarly defined. The heterogeneity term μ_i is assumed to be mutually independent of x_i, and is ascertain to be standard normal distributed. The log-likelihood function is

$$\begin{aligned}\ln L_i &= \sum_{i=1}^{n} \Bigg\{ \mathbf{1}(y_i = 1)\ \ln \int Pr(y_i = 1 \mid x_i, \mu_i) \mathrm{d}\varphi(\mu_i) \\ &\quad + \mathbf{1}(y_i = 0) \ln \left[1 - \int Pr(y_i = 1 \mid x_i, \mu_i) \mathrm{d}\varphi(\mu_i) \right] \Bigg\}, \end{aligned} \tag{8}$$

where individual heterogeneity should be integrated out following its probability distribution $\varphi(\mu_i)$ (i.e. standard normal). For this purpose, we compute the integration by taking the average over a number R of pseudo random draws for μ_i^r.[10] Estimates for β and the additional parameter σ are obtained by maximum likelihood.

We compare two nested models, without and with unobserved heterogeneity by calculating the likelihood ratio test. As shown in Table 2, the test statistic is very low, 0.012, which is much lower than the 5% critical value of the $\chi^2(1)$ distribution, i.e. 3.84. Therefore, the model without unobserved heterogeneity (as presented in Section 4) is preferred.

5.2 Endogenous regressors

It should be noted that some explanatory variables can be potentially endogenous. In particular, the presence of omitted variables and the possible reverse causality can induce the endogeneity of LN REVENUE and EXTENSION. Omitted factors can cover other household's characteristics, production technology, and policy variables that are not observed in the data. The reverse effect stems from the fact that the adoption of organic tea production can help households to improve their income one the one hand, and can motivate their participation in agricultural extension programs set up by the government. Including the question of regressor endogeneity in nonlinear models (such as the logit model here) is a relatively recent advance in econometrics. We test the endogeneity of LN REVENUE and EXTENSION by implementing the following two-step procedure of Wooldridge (2014).

1. First, we make an OLS regression for LN REVENUE on all of the explanatory

[10] The expression of this estimator is given by $(1/R)\sum_{r=1}^{R} Pr(y_i = 1 \mid x_i, \mu_i^r)$. In estimation, we define $R = 100$, given that other values ($R = 50, 200$) do not change the results. Further details can be found in McFadden and Train (2000).

variables above (except EXTENSION) and a set of excluded instruments. For EXTENSION which is a binary variable, we make a probit regression on the same set of explanatory variables (except LN REVENUE) and a set of excluded instruments. We observe that the linear regression for LN REVENUE looks like a production function whereas the probit regression for EXTENSION corresponds to the usual participation equation. We use the same set of excluded instruments for both of them, i.e. log of labor, use of chemical fertilizers, and use of organic fertilizers. The step allows to compute the residuals for the first regression, $\hat{u}_i$, and the generalized residuals for the second regression, $\hat{v}_i = w_i \lambda(z_i' \hat{\gamma}) - (1 - w_i)\lambda(-z_i'\hat{\gamma})$ where w_i is the indicator for extension participation (EXTENSION = 1) and λ is the inverse Mills ratio ($\lambda(.) = \phi(.)/\Phi(.)$, ϕ and Φ being respectively the density and cumulative probability of the standard normal distribution).

2. Secondly, we perform the usual logit regression (with and without unobserved heterogeity) as described above with two additional explanatory variables, $\hat{u}_i$ and $\hat{v}_i$, computed in the previous step. The endogeneity of LN REVENUE and EXTENSION is therefore tested by using robust Wald test for the null hypothesis that the coefficients of $\hat{u}_i$ and $\hat{v}_i$ are jointly zeros. The test is called '*robust*' because it is based on robust variance-covariance matrix. The test statistic corresponds to a $\chi^2(2)$ distribution.

Table 2 reports that the robust Wald test statistic is 1.86 and that the corresponding p-value is 0.39. Thus, we cannot reject the null hypothesis of absence of regressor endogeneity and conclude that LN REVENUE and EXTENSION are exogenous. Again, this finding confirms the domination of the model presented in the previous section.

5.3 Multiple data imputations

Omitting missing values in empirical analysis may lead to biased and inconsistent parameter estimates. Scholars recognize that failings to deal with missing data might cause substantial parameter bias and influence the efficiency and explanatory power of the results (Rose and Fraser, 2008; Cheema, 2014). The problem of missing data is ubiquitous in social research and has received widespread attention in a large number of research disciplines (Moss and Mishra, 2011; Ghosh, 2011; Gómez-Carracedo et al., 2014; Cheema, 2014; Rezvan et al., 2015; Li et al., 2015; Kalaycioglu et al., 2016). The current literature discusses many imputation methods, ranging from simple mean imputation–where missing values of a variable are replaced by the mean of non-missing data– to more complex parametric and semi-parametric imputation methods. The latter involves the specification of a model for the missing values given the observed data and drawing imputed values from the posterior predictive distribution that can be different for each missing value (Morris et al., 2014; Heitjan and Little, 1991; Schenker and Taylor, 1996).

Multiple imputations methodology can be a powerful tool if the measures in the imputation model are associated with the missing values to produce less biased estimators in the presence of missing data. One major concern is whether the missing data is missing completely at random. In other words, missingness does not depend on the variables in the data set (Little, 1988). Multiple imputations analysis needs to be conducted very carefully as consistent results can only be obtained when data is missing completely at random (MCAR). MCAR means that there is no relationship between the data point and the missing data. Thus, MCAR assumes that the probability of the observation being missing does not depend on observed and unobserved measurement. Deleting missing data would be desirable if MCAR assumption does not hold. Therefore, we employ Little MCAR test to assess whether the missing values in our database are missing completely at random. MCAR test is statistically significant at 1% level ($p_{value} < 0.001$) and confirms the MCAR hypothesis.

Missing values in our survey data accounts for 22%. Survey respondents in our sample might have left items blank on the questionnaire due either to lack of understanding, knowledge or unwillingness to answer the question. We apply predictive mean matching (PMM) method which imputes a value randomly from a set of nearest observed value whose predicted values are closest to the predicted value from a regression model (Horton and Kleinman, 2007). In other words, the imputation for a farm household with a missing value in a variable is replaced by the observed value of the farm household with the nearest predicted value. This method relax some of the parametric assumptions and is widely known to improve the robustness of inference with missing data to misspecification of the imputation model and ensures that the imputed values are plausible if the normality assumption is violated (Horton et al., 2003; Morris et al., 2014; Vink et al., 2014). Appendix A provides summary statistics of the missing data pattern and the distribution of observed and imputed data.

$$- - - \Big[\text{Table 3 here}\Big] - - -$$

We compute some information criteria (AIC and BIC) to compare different models (with and without unobserved heterogeneity) estimated with either original or imputed data. The computed values are reported in Table 3. The result confirms that the model without unobserved heterogeneity and estimated with original data (i.e. the model presented in Section 4) is the best among the competing models as it corresponds to the lowest values of AIC and BIC.

5.4 Goodness of fit

We assess the goodness-of-fit of the selected logit model presented in Section 4. Firstly, the pseudo R^2 is 0.389, which roughly means that the whole set of explanatory variables can explain about 39% of variation in the household's choice. This test is also consistent with the test for model's significance, which rejects the hypothesis that all the coefficients of the model are jointly zeros (test statistic $\chi^2(11) = 33.26$ with p-value $= 0.001$).

$$- - - \Big[\text{Table 4 here}\Big] - - -$$

Additionally, we verify the percentage of correctly predicted (classified) observations. The overall rate of correct classification is estimated to be 87.19%. Table 4 summarizes the number of correctly predicted observations about the adoption of organic tea production. The observations of the organic tea production group is to 95.09% correctly predicted and the conventional tea production group is to 45.00% correctly predicted. In general, the classification is sensitive to the relative size of each component group and thus might favor the classification of the larger group. This holds for our data. Despite of this general observation, a high number of wrong predictions for conventional tea still means that some further investigations are needed to improve the model (e.g., additional variables, alternative specifications, etc.).

6 Conclusions

This articles delves into the main determinants to adopt organic tea production in Northern Vietnam. We employ an empirical analysis using logit model. The robustness of the results are assessed for three important statistical questions (regressor endogeneity, unobserved heterogeneity and missing data). The model is estimated using farm household data from a sample of both organic and conventional Vietnamese farms specialized in tea production. Data was gathered through survey questionnaire and face to face interviews in 2013 in Vietnam.

The dependent variable in the logit model is the farm household's choice to adopt organic tea cultivation. We consider several explanatory variables involving farm household and farm characteristics as well as exogenous and territorial factors. The empirical findings are consistent with the theoretical predictions. Four determinants were identified to increase the likelihood of adopting organic farming. Farm households with higher revenues, belonging to a tea association, being consulted by extension agents and located in Phu-Tho province are significantly more likely to adopt organic tea farming. The results of the basic model are largely robust and are not influenced by unobserved heterogeneity and endogeneity. Increasing the sample size by applying multiple imputations method could not alter the quality of the results.

In the last years, the Vietnamese government has set up specialized agricultural extension programs and practical training measures to encourage farm households to develop organic farming. These policy actions have proven to be very effective and play a crucial role in the support for organic tea cultivation. On the other hand, other forms of support need to be improved, such as guaranteeing a fixed organic tea price, relieve certifications costs or helping farmers to distribute and export organic tea products.

Further efforts have been put forward to address the lacking marketability and distribution of organic products. The certification scheme *VietGAP* has been initialized by the Ministry of Agriculture and Rural Development in 2008 to increase the quality and enhance the exports of food products (Ha, 2014a; Van Bac et al., 2017). However, third party certification schemes are cost-intensive for producers/farmers and the standard obligations are very often administratively burdensome. As a consequence, small-scale farmers and poor farm households are more reluctant to switch to organic farming and inclined to not comply with certification standards (Van Bac et al., 2017). An alternative solution, named Participatory Guarantee System (PGS), represents the direct participation of farmers, producers, government, private sector, supporting organizations (NGOs) and consumers in the process to guarantee the quality of safe agricultural products. This form of quality assurance system builds on trust, social networks and knowledge exchange and is adapted to local markets and short supply chains (PGS-Vietnam, 2013; Ha, 2014b; Willer and Lernoud, 2016). Our findings reveal that poorer farm households are more prone to adopt organic farming. Alternative policy packages need to be addressed to support those farmers who do not have sufficient financial capital to bear the risks of adopting new agricultural practices.

Several limitations of our analysis need to be highlighted. It must be acknowledged that we chiefly focus on the production side of the organic tea farming. To provide a better understanding about the potential of the domestic and foreign markets it would be beneficial to analyze market access, the distribution channels, the (local) food chain and consumer willingness to pay for organic tea products. Further, several explanatory variables, including wage labor forces, environmental concern, subsidies to produce organic tea are lacking in our analysis due to the limitation of the questionnaire. To overcome thus these limitations, more research appears necessary. In a next step, future research should help to address the question of the environmental, social and economic impact of organic tea production on farmer's livelihoods by applying program evaluation methodologies.

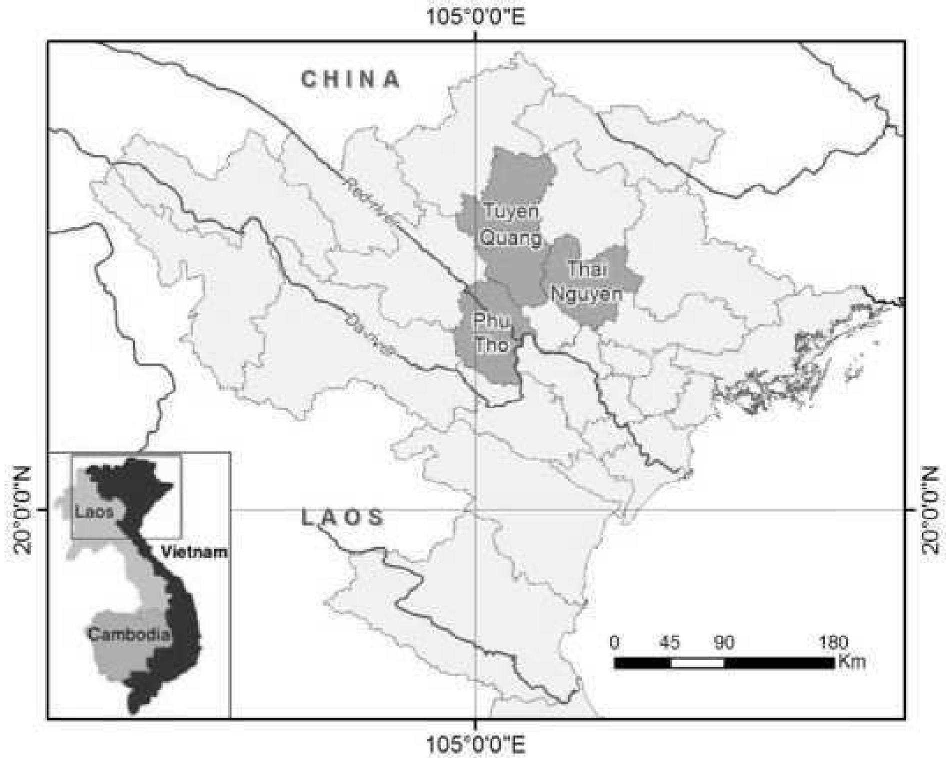


Figure 1: Geographical location of the three provinces in Northern Vietnam

Table 1: Summary of variables included in the estimations

Variable name	Definition	Nature	Mean	Std. Dev.	Min.	Max.	Obs.
CHOICE	Cultivation of organic tea		0.20	0.40	0	1	216
	(1 if yes, 0 otherwise)	dummy					
REVENUE	Farm household revenues per cultivated tea area (million VND)	continuous	65.78	67.09	2.13	403	241
LAND	Farm size measured in hectares	continuous	0.58	0.60	0.01	4.5	241
LABOR	Total labor employed in tea production (persons per day)	continuous	225.01	545.75	5	7863	241
EXPERIENCE	Years of experience in tea cultivation of the household head	continuous	29.75	13.84	2	64	241
HHSIZE	Household size (persons living in the household)	continuous	4.35	1.14	2	10	239
HEDUC	High educational level of the household head (high school or above)		0.33	0.47	0	1	241
	(1 if yes, 0 otherwise)	dummy					
MINORITY	Head of the household corresponds to a minority		0.11	0.31	0	1	241
	(1 if yes, 0 otherwise)	dummy					
GENDER	Head of the household's gender		0.43	0.50	0	1	241
	(1 if male, 0 otherwise)	dummy					
TASSO	Farm household is member of a tea association		0.37	0.48	0	1	215
EXTENSION	Farm household has been consulted by extension agents		0.72	0.46	0	1	241
	(1 if yes, 0 otherwise)	dummy					
$FERT_{CH}$	Farm household applies only chemical fertilizer		0.74	0.44	0	1	241
	(1 if yes, 0 otherwise)	dummy					
$FERT_{ORG}$	Farm household applies only organic fertilizer		0.48	0.50	0	1	240
	(1 if yes, 0 otherwise)	dummy					
PROVINCE 1	The farm is located in the Tuyen-Quang province		0.30	0.46	0	1	241
	(1 if yes, 0 otherwise)	dummy					
PROVINCE 2	The farm is located in the Phu-Tho province		0.13	0.34	0	1	241
	(1 if yes, 0 otherwise)	dummy					
PROVINCE 3	The farm is located in the Thai-Nguyen province		0.57	0.49	0	1	241
	(1 if yes, 0 otherwise)	dummy					

Table 2: Estimation results for the logit model

Variable	Coefficient	Robust Std.Err.	Marginal effect	Std.Err.
LN REVENUE	1.116**	0.426	0.088**	0.031
LN LAND	0.193	0.405	0.015	0.032
MINORITY	1.271	0.916	0.154	0.154
HEDUC	-0.0884	0.497	-0.007	0.038
GENDER	-0.116	0.536	-0.009	0.043
HHSIZE	0.174	0.167	0.014	0.013
EXTENSION	1.091*	0.567	0.073**	0.036
EXPERIENCE	-0.0190	0.0179	-0.002	0.001
TASSO	2.373**	0.602	0.252**	0.081
TUYEN-QUANG	-0.612	0.943	-0.045	0.064
PHU-THO	2.417**	0.914	0.361*	0.188
Intercept	-8.110**	2.751	–	–
Number of observations	203			
Ln Likelihood	-61.514			
Pseudo R^2	0.389			
Model's significance: Wald test[a]	$\chi^2(11) = 33.26$, p-value = 0.001			
Endogenous regressors: Wald test[b]	$\chi^2(2) = 1.86$, p-value = 0.39			
Unobserved heterogeneity: LR test[c]	$\chi^2(1) = 0.012$ p-value = 1			

Notes. Significant level: ** 5%, * 10%. [a] Test for the model's significance with the null hypothesis that all the coefficients (except the intercept) are jointly zeros (under the null the test statistic follows a $\chi^2(11)$). [b] Test for endogeneity of LN REVENUE and EXTENSION (under the null of absence of endogeneity, the test statistic follows a $\chi^2(2)$). [c] Test for existence of unobserved heterogeneity (under the null of absence of unobserved heterogeneity, the test statistic follows a $\chi^2(1)$.

Table 3: Information criteria

	Without unobserved heterogeneity	With unobserved heterogeneity
Original data	$AIC = 147.03$	$AIC = 149.02$
	$BIC = 186.79$	$BIC = 192.09$
Imputation data	$AIC = 220.63$	$AIC = 226.63$
	$BIC = 262.45$	$BIC = 267.94$

Table 4: Classification table

Prediction	Organic Tea	Conventional Tea
Correct	95%	45%
Wrong	5%	55%

A Multiple Data Imputations

We provide additional numerical information and graphical illustration about the multiple data imputations involving the analysis of missing data pattern and the distribution of original and imputed data. Table 5 summarizes that 203 observations are completed, 10 observations are missing for the dependent variable CHOICE, 2 observations are missing for the variable HHSIZE, 11 observations are missing for the variable TASSO, 15 observations are missing for both variables CHOICE and TASSO. The percentage of missing values in the survey data represents about 22%.

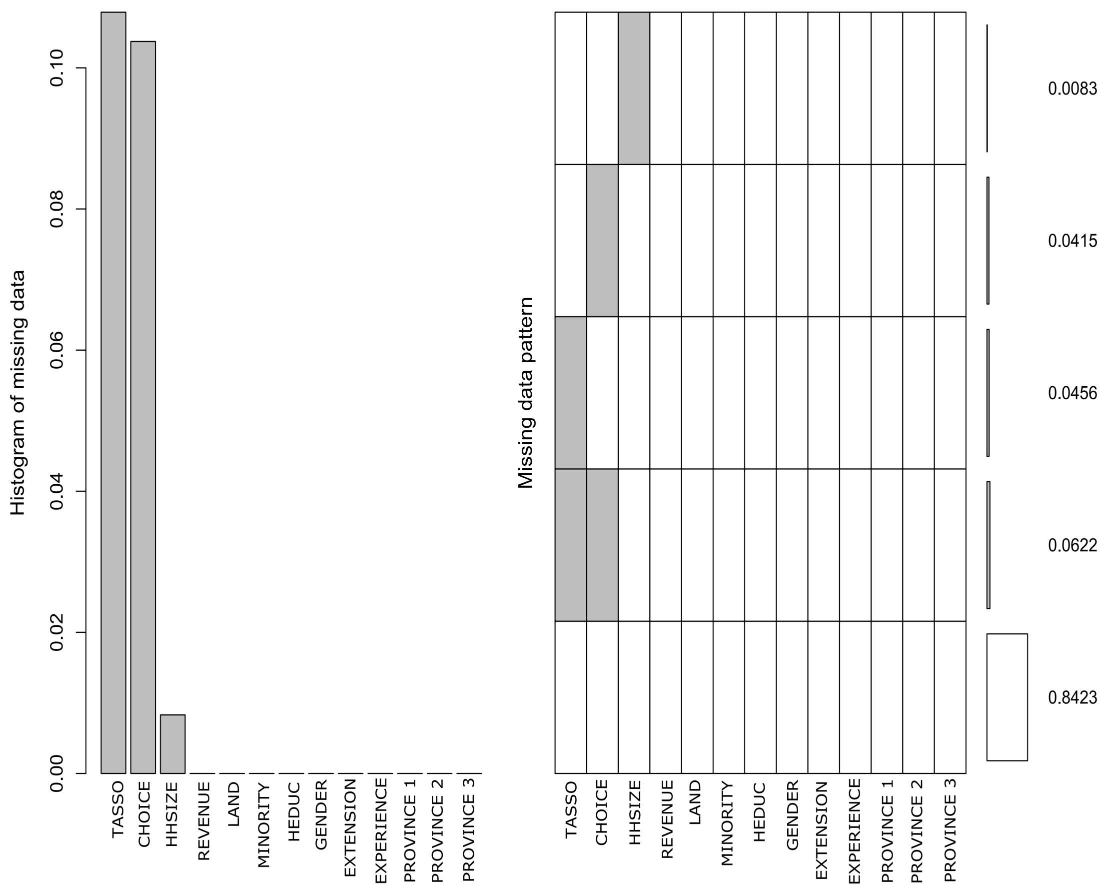
Table 5: Pattern of missing data

Observation	203	10	2	11	15	-
CHOICE	1	0	1	1	0	25
REVENUE	1	1	1	1	1	0
LAND	1	1	1	1	1	0
MINORITY	1	1	1	1	1	0
HEDUC	1	1	1	1	1	0
GENDER	1	1	1	1	1	0
EXTENSION	1	1	1	1	1	0
EXPERIENCE	1	1	1	1	1	0
PROVINCE 1	1	1	1	1	1	0
PROVINCE 2	1	1	1	1	1	0
PROVINCE 3	1	1	1	1	1	0
HHSIZE	1	1	0	1	1	2
TASSO	1	1	1	0	0	26
Missing data	0	1	1	1	2	53

Note that each row corresponds to a missing data pattern (1=observed, 0=missing).
The last column and row contain row and column counts, respectively.
Source: Own calculations

The descriptive statistics from Table 5 are plotted graphically in Figure 2. The figure depicts two common graphic charts. The right-hand-side chart demonstrates that 84.23% of the data does not comprise missing observations, 6.22% of the data contains missing data for both variables jointly TASSO and CHOICE, 4.56% of the data involves missing data for the variable TASSO, 4.15% includes missing data for the dependent variable CHOICE and 0.83% of the data entails missing data for the variable HHSIZE.

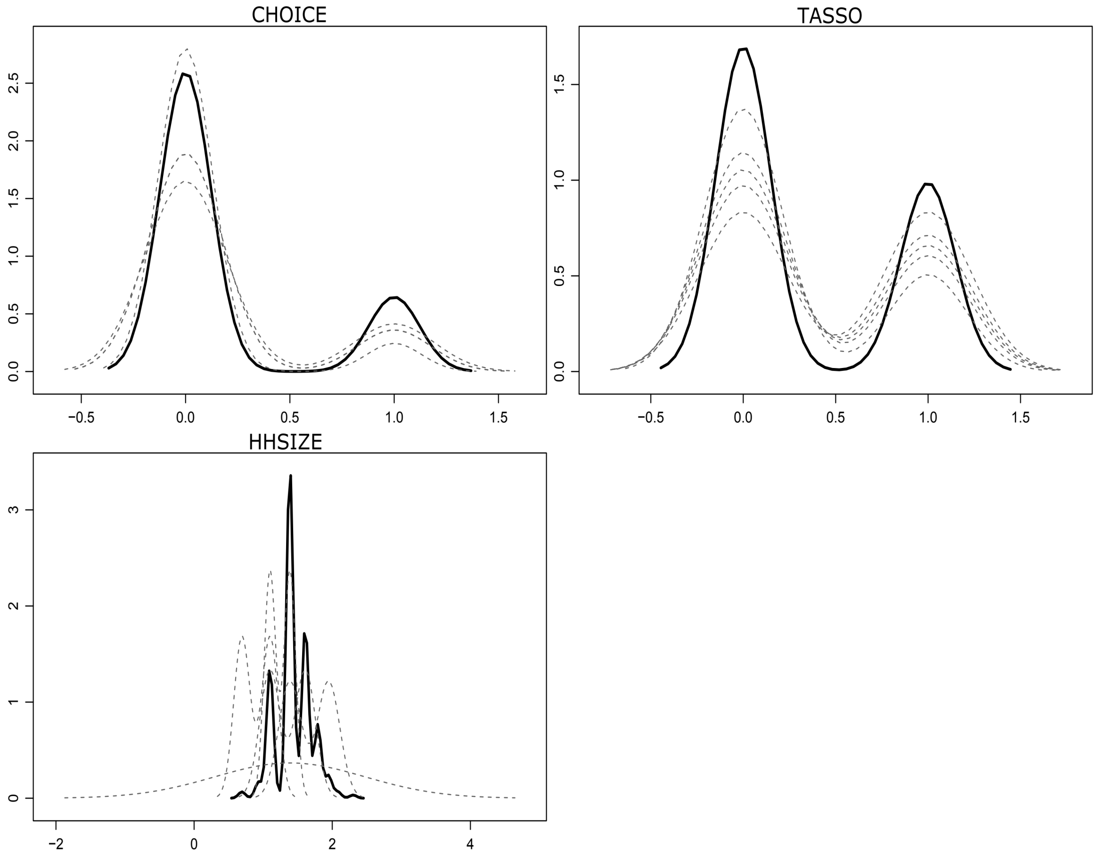
Figure 2: Missing data pattern



"White" and "grey" correspond to the observed and missing data, respectively
Source: Own calculations

Figure 3 visualizes the density of the observed (solid line) and the imputed data (dashed line). It is important to bear in mind that the assumption of missing completed at random (MCAR) holds if the imputed and observed density distributions are akin. Figure 3 clearly demonstrates that the MCAR assumption holds for our dataset.

Figure 3: Imputation by predictive mean matching



"Solid" and "dashed" line correspond to the observed and imputed data, respectively
Source: Own calculations

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