Coffee Farmer Preferences for Sustainable Agricultural Practices: Findings from Discrete Choice Experiments in Vietnam

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Abstract

Despite the proven benefits of sustainable agricultural practices (SAPs), adoption rates among farmers are still low, especially in developing countries. This paper seeks to assist policymakers devise approaches to encourage adoption by identifying the attributes of SAPs that can motivate Vietnamese coffee farmers to adopt them in production. Vietnam is the world's second largest coffee producer and the sector supports the livelihoods of over half a million people in the country. We conduct two different types of discrete choice experiments with over 300 Vietnamese coffee farmers to identify their SAP preferences. We analyse the data using cluster analysis and generalised multinomial logit models. The results are consistent across our different approaches. They show that these farmers have the strongest preferences for SAPs that can provide higher profits, lower risks (of output loss) and higher environmental benefits. These attributes received mean part-worth utilities of 0.251, 0.250 and 0.239 respectively. Attributes capturing the increase in daily operating efforts and time required to set up such practices are less important considerations. Further, the farmers are willing to pay on average between 26 to 32 million VND per hectare per year for a one level reduction in the risk of output loss and earn 15 million VND per hectare per year less in profits to achieve a one level increase in environmental benefits.

Keywords: Discrete choice experiments, sustainable agricultural practices, coffee, Vietnam

JEL classifications: Q12, Q18

1. Introduction

In order to reach the United Nations' Sustainable Development Goals (SDGs) by 2030, farmers globally need to adopt sustainable agricultural practices (SAPs). This paper contributes to the existing literature by eliciting the preferences of Vietnamese coffee farmers using two different types of discrete choice experiments (DCEs). Farmer preferences for specific SAP attributes are identified together with their willingness to pay for these. This provides policymakers with important information to encourage SAPs for coffee production in Vietnam and elsewhere.

Attention to SAPs is intensifying. Globally, there are increasing concerns with respect to food safety and the environmental impacts of conventional farming[1]. The World Health Organization (WHO) (2020) estimates that every year 420,000 people die and 600 million fall ill from eating contaminated food. The use of agrochemicals is claimed to pose hazards to human health (Sanders, 1999). The WHO (2018) states that the use of pesticides (especially dichlorodiphenyltrichloroethane) can cause deaths by poisoning, particularly in low and middle income countries. According to the Food and Agriculture Organization (FAO) (2017b), the agricultural sector accounts for about 20% of global greenhouse gas emissions. These emissions come from the use of agrochemical inputs and waste from agricultural production. Other environmental impacts include deforestation, desertification, methane emissions, the pollution of water supplies, eutrophication and increasing water scarcity.

SAPs can assist in alleviating the impacts of unsustainable farming while maintaining productivity and improving product quality (Gathala et al., 2020; Pretty et al., 2006; Teklewold,

[1] Rasul & Thapa (2003) define conventional agriculture as "…the agricultural system broadly characterized by intensive use of land with high external inputs including high-yielding varieties of seeds, inorganic fertilizers and pesticides, irrigation, monocultures of crops and low diversity" (p.1738).

Kassie, Shiferaw, et al., 2013)[2]. SAPs have been considered a win-win strategy especially for lower income countries since they can improve food security while addressing environmental issues (Zeweld et al., 2017). Some practices, such as improved seed varieties, integrated pest management, crop rotation and tillage, bring economic benefits via improved yields and household incomes (M. Kassie et al., 2013; Manda et al., 2016). Scholars confirm that in the long term, sustainable agricultural systems are more effective than conventional farming systems in reducing soil erosion and maintaining soil productivity (Reganold et al., 1987). Also, by encouraging the application of locally available resources (e.g., manure, organic fertiliser), SAPs significantly reduce transaction and other input costs. They can therefore bring higher, long-term economic benefits to farmers while enhancing food security and economic growth (Asfaw et al., 2012; Teklewold, Kassie, & Shiferaw, 2013).

However, the adoption rate of SAPs is still low, particularly in developing countries (Tey, 2013) which are the biggest agricultural producers of common commodities such as cereal and coffee (FAO, 2018). Studies examining the household adoption of SAPs typically use household level survey data in which adoption depends on plot and farmer characteristics such as land quality, slope, farm size and education (M. Kassie et al., 2015; Liu & Huang, 2013; Teklewold, Kassie, & Shiferaw, 2013). There is often a significant correlation between having resources such as livestock and off-farm income with the likelihood of adopting SAPs (Wollni et al., 2010). Moreover, social capital has often been found to be a significant factor in the adoption of SAPs in developing countries (Markussen & Tarp, 2014; Pham et al., 2021; Wossen et al., 2015). Krah et

[2] In this paper, we define SAPs as systems that use alternative techniques and technologies to replace unsustainable practices and agrochemical inputs used in conventional farming, to achieve three independent but interrelated goals (economic, ecological and social) for current and future generations.

al. (2019) argue that the reluctance to adopt SAPs may be due to the constraints that farmers face or a lack of incentives for adoption.

To encourage adoption, the design of SAPs must reflect farmer constraints and preferences. This requires a better understanding of the SAP characteristics that farmers value most (Bopp et al., 2019). DCEs provide a useful approach which can be used to evaluate individuals' preferences for goods and services that are not supplied by existing markets (Krah et al., 2019). They also allow for the estimation of the willingness to pay for non-monetary attributes (Johnson & Geisendorf, 2022; Ortega et al., 2016; Waldman et al., 2017). In the context of this paper, DCEs can provide an estimate of the relative importance of different SAP characteristics, achieved by farmers making choices between multiple-attribute goods or services (Adamowicz et al., 1998). DCEs have already been used to elicit preferences for crop varieties (Kassie et al., 2017), agricultural certification schemes (Lemeilleur et al., 2016) and agricultural insurance against extreme weather (Doherty et al., 2021). Specifically, Jaeck & Lifran (2014) and Owusu Coffie et al. (2016) used DCEs to investigate farmer preferences for SAPs for rice production in France and Ghana respectively. DCEs have also been applied to identify farmer preferences for maize varieties by Kassie et al. (2017), potato farming systems by de Brauw & Eozenou (2014) and recirculating aquaculture systems in Vietnam by Ngoc et al. (2016). Discerning the attributes that farmers value most can assist policymakers in providing incentives for SAPs adoption that meet farmer demands (Blazy et al., 2011; Krah et al., 2019). This is the objective of this paper.

We hypothesise that farmers' preferences for SAPs will be dominated by profitability and that existing SAP packages do not do enough to highlight this aspect, thus blunting the incentives for farmers to move away from their conventional agricultural practices. To test this hypothesis, this paper designs two DCEs to examine coffee farmer preferences for SAP attributes in the context of Vietnam. The first uses *pairwise rankings* whereby two hypothetical SAPs are differentiated with information on just two attributes at a time[3]. The second uses *stated preference choice sets* whereby participants choose between two hypothetical SAPs (or choose between these and the status quo) that have information across all the different attributes[4]. Mankad (2016) states that the complexities surrounding the definition of a sustainable agricultural term (e.g., biosecurity practices) may influence farmers' decision making. Thus, an advantage of the pairwise rankings design is simplifying a farmer's choice by providing them with information on just two attributes at a time. If, however, participants are able to absorb and consider information on all of the different attributes across two five-attribute alternatives, arguably the use of choice sets is more appropriate. If the two different approaches provide similar results regarding the importance of attributes, we can conclude that our findings are robust. To the authors' knowledge, this is the first study to apply both approaches to the same set of participants to examine the sensitivity of findings to the type of DCE used.

Results from this study suggest that coffee farmers in Vietnam have the strongest preferences for SAPs that provide higher profits but also higher environmental benefits and lower risk of output loss. They are willing to pay on average between 26 to 32 million VND per hectare per year for a one level reduction in the risk of output loss. They are also willing to accept a reduction of about 15 million VND per hectare per year in profits to achieve a one level increase in environmental benefits. The time required to establish new SAPs and the daily effort needed to manage SAPs are two other attributes that are less important. Preferences for SAPs are also

[3] See Hansen & Ombler (2009) and Graff & Mcintyre (2014) for details of the PAPRIKA technique used in pairwise rankings design.
[4] See Owusu Coffie et al. (2016) and Jaeck & Lifran (2014) for the application of stated preference choice sets.

heterogenous, depending on farmer characteristics such as age, education and location. These findings suggest that when introducing SAPs to farmers, the focus should be on explaining how such practices can increase profits and environmental benefits and how to prevent output loss as such information is important to them. Policymakers should also consider incentives that support farmers to overcome the burdens of SAPs adoption, including the risk of output loss, increased time to set up and increased efforts to manage new SAPs.

In sum, it is increasingly important that farmers, globally, adopt SAPs due to environmental pressures. Yet adoption rates remain low. This paper seeks to identify the SAP preferences of coffee farmers in Vietnam so that policymakers can devise more effective interventions to improve adoption rates. It does so by running two different types of DCEs with the same farmers to provide robust findings on their relative preferences for different SAP attributes and their willingness to pay for these.

The remainder of this paper is structured as follows. Section 2 introduces the context of study, which is coffee production in Vietnam. Sections 3 and 4 describe the design of the DCEs and the data collection process respectively. Section 5 details the different empirical methodologies used to analyse the data. Section 6 presents and interprets the results. Section 7 concludes and highlights some policy implications.

2. Coffee Production in Vietnam

Vietnam is the second largest coffee exporter in the world. It produces approximately 28 million 60-kilogram bags per year, 90% of which are exported, predominantly in the form of green beans (The sustainable trade initiative - IDH, 2019; International Coffee Organization - ICO, 2017; Tran, 2016, 2017, 2019). The country accounted for 19% of global Robusta coffee in the

2015/2016 production season (ICO, 2016). Nationally, there are about half a million Vietnamese farmers participating in the sector, which contributes to 3% of Vietnam’s GDP (GSO 2015).

However, current coffee production in Vietnam is viewed as unsustainable and susceptible to the impacts of climate change. First, ageing coffee trees is constraining production (Chapman, 2014; CIEM, DOE, ILSSA, & IPSARD, 2011; ICO, 2017). Among the 600,000 hectares under cultivation in Vietnam, nearly 30% of coffee trees are between 15 - 20 years old and about 20% are more than 20 years old (ICO, 2019). Ageing trees are not resilient to pests and diseases, and produce lower yields and lower quality beans (The Committee on Sustainability Assessment (COSA), 2013). Second, farmers in the Central Highlands region applied an average of 1.56 tonnes of chemical fertiliser per hectare of land in 2014 (Ho et al., 2017). This figure is approximately four times higher than the recommended usage level of nitrogen, phosphorus and potassium (NPK) (Tiemann et al., 2018). Overuse of such agrochemical inputs causes serious environmental problems and foodborne diseases (Hoang & Nguyen, 2013). Third, current production is cost-inefficient compared to some sustainable production (i.e., production that meets the requirements of a certified program such as 4C, organic or fair trade) and has lower value-add compared to certified coffee beans (Quoc Ho, 2018). Fourth, production is highly water dependent. Coffee farmers in Vietnam exploit ground water (freely) for production. The coffee sector contributes to water scarcity but is also affected by it. Drought and water shortages have been shown to significantly reduce coffee production in Vietnam (Tran, 2016). Finally, the impacts of climate change, increasing crop failures and the high volatility of coffee prices are all placing farmers’ welfare at risk (Bisang et al., 2016; The sustainable trade initiative - IDH, 2019).

Not only is there an environmental case for the adoption of SAPs by coffee farmers in Vietnam, but there is also a strong business case. Minimising chemical and water use will lead to more cost-effective coffee production in the longer term. Adopting SAPs is one way to move towards sustainable certified coffee farms which can perform better than their non-certified counterparts in both economic and environmental aspects (Ho et al., 2021). Coffee is mostly consumed in developed countries where consumers are willing to pay a higher price for organically and/or ethically produced coffee (Hainmueller et al., 2015). Thus, the adoption of SAPs in the coffee industry can bring direct benefits to farmers and consumers in Vietnam as well as to the overall economy.

3. Experimental design

DCEs have become a common technique to address a wide range of policy issues in transport (Hensher et al., 2005), environmental (Hanley et al., 2001) and health (Bekkler-Grob et al., 2012) economics. They also provide a useful approach to elicit farmer preferences for new agricultural technologies. They allow researchers to simulate market and production circumstances by creating hypothetical scenarios in which respondents make multiple decisions. Respondents are presented with scenarios that include two or three alternatives, each consisting of multiple characteristics or attributes. Each attribute has different levels. Respondents choose their preferred option from the alternatives provided. By choosing their most preferred options among a series of alternatives, respondents reveal their weights or preferences for each attribute. In some designs, the status quo is also included, allowing a respondent to not (be forced to) choose between the alternatives (Bonnichsen & Ladenburg, 2015; Samuelson & Zeckhauser, 1988).

In the first stage of designing our DCEs, we established the attributes that coffee farmers consider in their production decisions and then assigned levels to each. To do so, we reviewed related literature and interviewed agricultural scientists and researchers at Otago University (New Zealand), the Western Highlands Agriculture and Forestry Science Institute (WASI, Vietnam) and

Tay Nguyen University (Vietnam). This enabled a better understanding of the appropriate SAPs and current state of SAP adoption in coffee farming in Vietnam[5]. The provisional list of attributes was then presented to coffee farmers in four focus group discussions, two each in Dak Lak and Lam Dong provinces in 2017. These two provinces are located in the Central Highlands of Vietnam and are the largest producers of coffee in the region (ICO, 2019). Each focus group hosted between nine and 13 farmers, comprising both adopters and non-adopters of SAPs.

Based on the feedback provided by these focus groups, the following five SAP attributes were finally selected for our DCEs: (1) the extent to which adoption increases profits, (2) the extent to which adoption increases environmental benefits, (3) the risk of output loss associated with adoption (the probability of a bad harvest), (4) the amount of time required to prepare (set up) the SAP, and (5) the level of daily effort required after adoption. All five attributes are in comparison to the status quo. Following the existing literature (e.g., Rao, 2014), we assigned three levels for each attribute[6]. The attributes, their levels and corresponding hypotheses regarding farmer preferences are presented in Table 1.

Information on the attributes and their levels were then entered into choice metric software to generate choice sets. As discussed above, this study employs both pairwise rankings and stated preference choice sets in the DCE design. The former is generated by the software package *1000minds*, which uses the "potentially all pairwise rankings of all possible alternatives" (PAPRIKA) algorithm (see Hansen & Ombler, 2009) to generate a series of choice sets, each with two alternatives from which participants must choose their preferred one. Although there are five

[5] See Table S3 of the supplementary document.

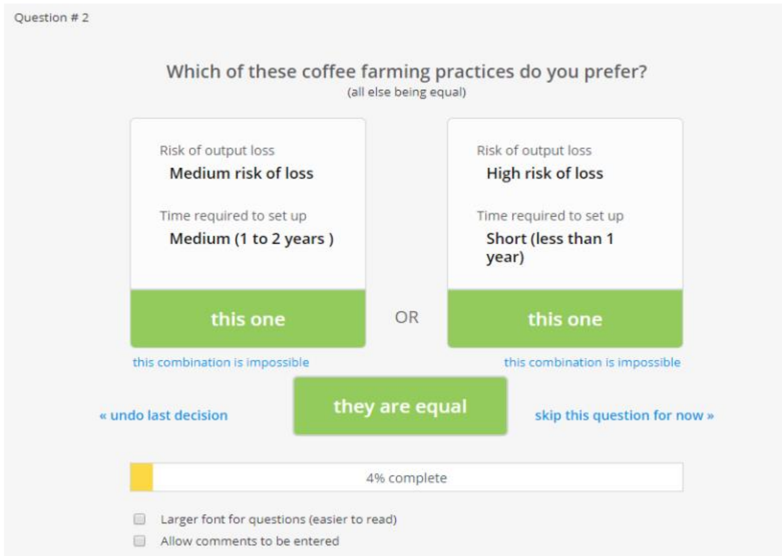
[6] Our numbers of attributes and levels conform with Rao (2014), who recommends a range of five to eight attributes for DCEs conducted in low and middle income countries, with between two and at most six levels.

attributes, the software presents participants with scenarios of just two attributes at a time, assuming the other three are the same across alternatives. In pairwise rankings there is always a trade-off between the two alternatives (through differences in the levels of the attributes). If a farmer cannot decide which alternative they prefer, they can choose a “they are equal” option. Figure 1 provides an example of a choice set generated by the *1000minds* software.

Table 1: SAP attributes and their levels

Attribute	Level	Hypothesis on farmer preference
Increase in profits	Low (10 million VND/ha/year) Medium (45 mil VND/ha/year) High (80 mil VND/ha/year)	The higher the profits, the higher the probability farmers will adopt the SAP
Increase in environmental benefits	Low Medium High	The higher the environmental benefits, the higher the probability farmers will adopt the SAP
Increase in the risk of output loss	High Medium Low	The higher the risk of output loss, the lower the probability farmers will adopt the SAP
The time required to set up	High (more than 2 years) Medium (1-2 years) Low (less than 1 year)	The higher the time required to set up, the lower the probability farmers will adopt the SAP
Increase in daily effort required	High Medium Low	The higher the daily effort required, the lower the probability farmers will adopt the SAP

Figure 1: Example of pairwise ranking choice sets



Once the experiment starts, the computer shows each participant a choice set which is randomly picked from a thousand pairwise ranking choice sets. Each time a participant chooses from a pair of scenarios, the PAPRIKA method applies the transitivity property to identify all other pairs of scenarios that can be ranked [7], thereby saving the participant being asked redundant questions (Feeny et al., 2019). In this study, with five three-level attributes, each participant made between 21 to 30 choices.

The second approach to DCE modelling employs stated preference choice sets. With five three-level attributes, there are 243 (i.e., 3^5) possible attribute-level combinations, which represents an unfeasibly large number of choice sets for each participant. There are different approaches that are commonly used to narrow down the choice sets (yet keep its efficiency in

[7] For example, if agricultural practice A is chosen ahead of practice B, and B is chosen ahead of practice C, then by transitivity, A must be chosen ahead of C. The method eliminates this third pair and any other pairs implied by transitivity

revealing participant preference) including full and fractional factorial techniques (Rose et al., 2008). Within these approaches, experimenters can adopt either an orthogonal design or a D-optimal design (Bliemer & Rose, 2010). The former aims to minimise the correlations between the attribute levels shown to the participants, while the latter aims to minimise the (co)variances in the parameter estimates by maximising the (Fisher) information obtained from each choice task (Rose & Bliemer, 2013).

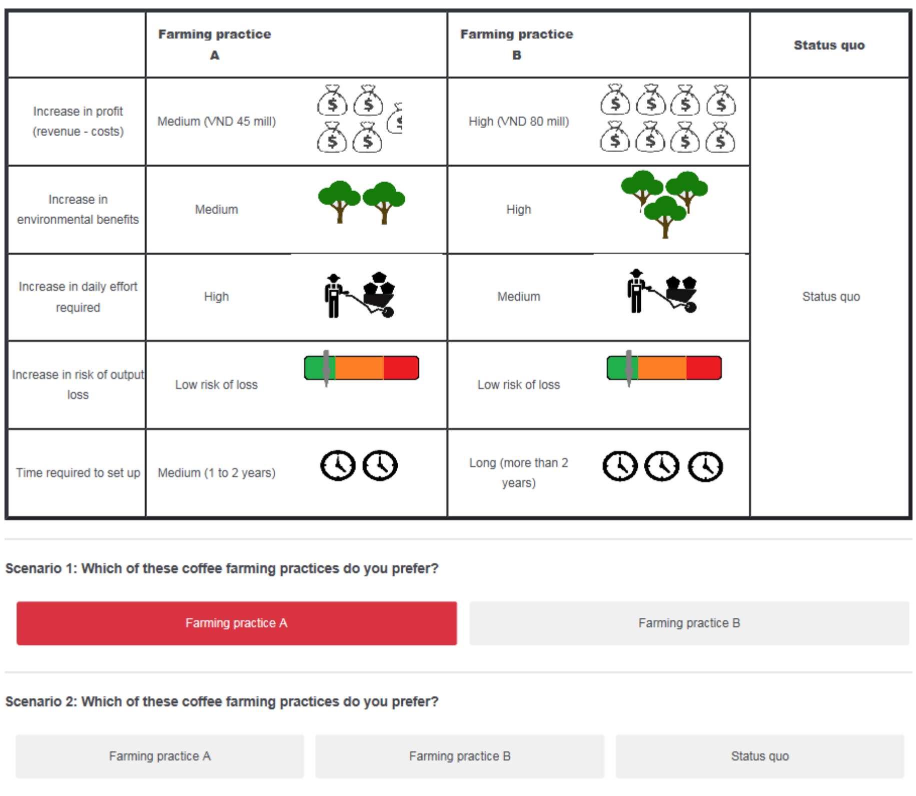
According to Bliemer & Rose (2010), the orthogonal design is the most popular technique in DCEs. It is adopted by this study using the software package *R* to generate 30 choice sets based on the Federov algorithm (Aizaki & Nishimura, 2008). This design ensures that there is no pairwise correlation between two attributes and limited correlation between levels of attributes while maintaining efficiency (Aizaki & Nishimura, 2008; Ryan et al., 2012)[8]. An advantage of this approach is that the data collected from participants can be used in regression analysis to deduce which SAP attributes are statistically significant.

Using stated preference choice sets, the inclusion of a status quo option potentially yields different results. The status quo represents the current practice of the participant. Without the status quo, participants are forced to choose one of the scenarios. They may therefore choose differently compared to when they can maintain their current practice. Since farmers can continue their current farming practice, having a *status quo* option in the choice sets is more realistic. Further, including a status quo option may avoid some potential biases in responses (Bonnichsen & Ladenburg, 2015; Samuelson & Zeckhauser, 1988). Following Jaeck & Lifran (2014), Kassie et al. (2017) and Owusu Coffie et al. (2016), this study creates two different choice sets, one with a status quo option

[8] The efficiency level for our orthogonal design in *R* is 78%.

and the other without. Figure 2 provides an example of a choice set with and without the status quo option. In the stated preference choice set experiments, the software *Qualtrics* randomly picks 10 out of the 30 choice sets to show to participants. This randomisation reduces the bias regarding farmers preferences for an SAP's attributes. For each choice set shown to them, participants made two decisions, the first between two sets of SAPs without a status quo option and the second with a status quo option (hence, in the second decision, they have an opt-out).

Figure 2: Example of stated preference choice sets



4. Data collection

The DCEs were conducted with coffee farmers located in the Dak Lak province. This province is the largest coffee producer in Vietnam (ICO, 2019), with the majority of farm households being dependent on coffee for their livelihoods. The adoption of SAPs is a pertinent issue in Dak Lak with coffee farmers experiencing soil degradation, water shortages and ageing trees. Previous attempts at encouraging SAP adoption in this province have proven largely unsuccessful due to being unattractive to the farmers.

A total of 305 coffee farmers from four districts of Dak Lak took part in the DCEs (including 30 farmers that took part in a pilot study). The four districts (i.e., Cu M'gar, Krong Nang, Krong Pak and Cu Kuin) and the villages within the districts were specifically selected based on the level of coffee production and exposure to ageing trees, drought and the inefficient use of inputs. Using coffee farmer population data from the Statistical Yearbook of Vietnam 2017 (General Statistics Office (GSO) 2017), a representative number of farmers, all non-adopters, were invited to participate in the DCEs from each district.

A list of all farming households in each village was used as a sampling frame. Approximately 30 farm-households were randomly selected in each village. The DCEs were conducted face-to-face with participants and were managed by the corresponding author (team leader) and six trained research assistants. To ensure a consistent and correct understanding of the SAP attributes, farmers were given clear information and instructions at the beginning of each experimental session (see the supplementary document). The team leader introduced the main purpose of the experiment, ensured participants understood the nature of the attributes and provided clear instructions on how to undertake the surveys. Each participant was surveyed privately with the support of one research assistant to answer any questions they may have. Socioeconomic and demographic information were also collected from the participants using the *Qualtrics* software following their completion of the DCEs.

5. Estimation methods

5.1. Estimation methods for pairwise rankings data analysis

The underlying PAPRIKA method of pairwise ranking choice sets involves respondents ranking all undominated pairs of all possible alternatives represented by the model. This method is simpler compared to traditional scoring methods in which respondents need to compare all attributes. Hansen & Ombler (2009) emphasise the importance of comparing PAPRIKA's accuracy relative to traditional methods. This study is the first to conduct DCEs using both the traditional method (based on random utility theory) and the PAPRIKA method for the same set of participants.

Based on participants' decisions in the pairwise ranking choice sets, *1000minds* provides the part-worth utilities (weights) for each of the five attributes at the individual (farmer) level. This enables the conduct of cluster analysis to identify groups of participants with similar preferences (see, for example, Feeny et al., 2019). Specifically, cluster analysis can be used to investigate whether there is heterogeneity in the preferences for SAP attributes which is driven by participants' socioeconomic and demographic characteristics.

When performing cluster analysis, it is important for researchers to decide how many clusters should be used to group participants. There are several ways to do this, including hierarchical and non-hierarchical clustering. Hierarchical clustering provides a "bottom-up" approach by initially pairing (clustering) each participant with another who is most alike with respect to their attribute preferences. The endpoint is a set of clusters, where each cluster is distinct from another but the individuals within each cluster are similar to one another. A common approach to hierarchical clustering is to generate a dendrogram and visually examine how may clusters appear to be in the data. The several different approaches to hierarchical clustering including single linkage, complete linkage, weighted average and Ward's distance. Blashfield (1976), Ferreira & Hitchcock (2009), Hands & Everitt (1987) and Milligan & Cooper (1988) have found that Ward's method performs significantly better than others. A popular non-hierarchical approach to clustering is the *k*-means approach, which clusters participants in a way that minimises intra-cluster distances from the cluster's mean or centroid. Under this approach, the researcher specifies the number of clusters in which to group the data. We adopted both approaches for our cluster analysis here.

5.2. Estimation methods for stated preference data analysis

The underlying theoretical framework used in analysing stated preference data is the random utility theory which is useful in explaining decisions in preference elicitation studies. The (latent) expected utility (*EU*) for person n obtained from choosing alternative j at time t can be specified as:

$$EU_{njt} = V\left(X_{njt}, Z_{njt}\right) = \beta X_{njt} + \gamma Z_{njt} + \varepsilon_{njt} \qquad (1)$$

$$n = 1, 2, \ldots, N; \qquad t = 1, 2, \ldots, T; \qquad j/k = 1, 2, \ldots, J$$

X_{njt} is a k-vector of observed attributes of alternative j (in our case a vector of five observed attributes) and other explanatory variables. X_{njt} may include alternative specific constants (ASCs), which capture persistence in the unobserved attributes for each alternative j at time t. If the average farmer views option j as having desirable unmeasured attributes, it will have a positive ASC. Z_{njt} is vector of interactions of choice attributes and farmer socioeconomic characteristics. Some studies do not add Z_{njt} as their main interest is for attributes of a good/service. β is a vector of utility weights, and $\varepsilon_{njt}{\sim}i.i.d$ provides the idiosyncratic error terms, which are assumed to be independently and identically distributed (IID) across coffee farmers.

Given that choice set T consists of J different SAPs, a rational farmer will choose alternative *i* if their subjective expected utility from choosing *i* is greater than any alternative *j*.

$$EU_{nit} > EU_{njt} \gg V_{nit} + \varepsilon_{nit} > V_{njt} + \varepsilon_{njt} \; \forall \; j \neq i, i, j \in T \tag{2}$$

Louviere, Hensher, & Swait (2000) note that the presence of the error term makes the choice random. Thus, the probability of choosing alternative i is greater than that of any other alternative in the choice set.

$$P(i) = P(V_{nit} + \varepsilon_{nit} > V_{njt} + \varepsilon_{njt}) \; \forall \; j \neq i, i, j \in T \tag{3}$$

$$P(i) = P(\varepsilon_{njt} - \varepsilon_{nit} < V_{nit} - V_{njt}) \tag{4}$$

Since the errors are assumed to be IID, we can represent the choice probability by

$$P(Y_n = i) = \frac{X_i\beta + Z_{ni}\gamma}{\sum_{j=1}^{J} \exp{(X_j\beta + Z_{nj}\gamma)}} \; i = 1,2, \ldots, J; i \neq j \tag{5}$$

Where Y_n is a random variable indicating the choice that smallholder *n* makes, and $\beta \; and \; \gamma$ are vectors of parameters to be estimated.

With choice set data, it is common to use a preference space (PS) approach adopting a conditional logit (CL) model and/or mixed logit (MIXL) model. More recent studies have used multinomial logit (MNL) or generalised multinomial logit (GMNL) which can better account for heterogeneity in farmers' preferences for unobserved attributes. The pros and cons of the different approaches are very well conveyed in Fiebig, Keane, Louviere, & Wasi (2010), G. T. Kassie et al.

(2017) and Owusu Coffie et al., (2016). In this paper, we adopted the GMNL due to its advantages in controlling for heterogeneity in the unobserved attributes of the SAPs. In Keane, Louviere & Wasi (2008), the GMNL model is described as the nested model which includes both nests MIXL and S-MNL. In this model, the utility of person n from choosing alternative j for choice occasion t is given by:

$$U_{njt} = [\sigma_n \beta + \gamma \eta_n + (1 - \gamma)\sigma_n \eta_n] x_{njt} + \varepsilon_{njt} \tag{6}$$

Where $\gamma = [0,1]$ is a parameter, σ_n is the scaling factor which is used to scale up or down proportionately across respondent n. Note, γ mediates the influence of both parameter and scaling heterogeneity as well as how the variance of residual heterogeneity varies with scale.

The estimation becomes GMNL-I if γ is set equal to 1, and GMNL-II if γ is set equal to 0. GMNL estimations are preferred over logit models because they can: firstly, consider ASCs which capture unobserved technology attributes; secondly, relax the IIA assumption in MNL; thirdly, control for heterogeneity of utility weights across individuals; and finally, consider the correlation in tastes across attributes, which is a limitation of MIXL. Based on this, eight different GMNL models were estimated[9]. A comparison of the AIC and BIC of the eight models showed consistency in terms of their findings. As such, we only discuss the results of the full GMNL model below.

In sum, to ensure our findings are meaningful and robust, our methodology includes consulting Vietnamese coffee farmers on the main attributes they take into account when

[9] They are: (1) Full G-MNL, (2) Full G-MNL with non-random ASC, (3) Full G-MNL with random ASC, (4) G-MNL-II (γ =0) with non-random ASC, (5) G-MNL-II (γ =0) with random ASC (i.e., GMNL uncorrelated errors), (6) G-MNL-I (γ =1) with no-random ASC, (7) G-MNL-I (γ =1) with random ASC, and (8) GMNL with correlated errors.

considering a SAP, adopting two different types of DCEs and rigorously analysing the data using the most appropriate econometric techniques.

6. Results and interpretation

6.1. Descriptive statistics

Table 2 provides some descriptive statistics of the sample population for our two DCEs. There was no statistically significant difference in the gender of participants with 50.8% being male. The average age of farmers was about 44 years and most had finished secondary school. The characteristics of our sample are similar to that of the Vietnam Household Living Standards survey and the Vietnam Access to Resources Household survey (Tarp, 2017). The average household size is between four and five members with an average of three adults per household. The average farm size is 1.3 hectares, over 80% of which is devoted to coffee production. Coffee productivity was approximately three tonnes per hectare, which is slightly higher than the national average of 2.87 tonnes per hectare (Tran, 2019). Farmers cultivated an average of 300 coffee trees per hectare, the majority of which were more than 20 years old. Approximately 72% of participants reported a loss in productivity over the past 10 years due to extreme weather conditions (water shortage, drought and disaster), pests and/or diseases. Chemical fertilisers were universally applied by participants, while organic fertilisers were applied by 50%.

Table 2: Descriptive statistics of coffee farmers in sample

Variable	Description	Obs	Mean	Std. Dev.	Min	Max
District						
CuKuin	Cu Kuin district (1=Yes; 0=No)	305	0.100	0.300	0	1
CuMgar	Cu Mgar district (1=Yes; 0=No)	305	0.390	0.490	0	1
KrongNang	Krong Nang district (1=Yes; 0=No)	305	0.300	0.460	0	1
KrongPac	Krong Pac district (1=Yes; 0=No)	305	0.210	0.410	0	1
Household						
Gender	Gender of respondent (Male=1; Female=0)	305	0.508	0.501	0	1
Age	Age of respondent	304	44.882	13.519	18	78
Education	Level of education of the respondent (1=none; 2=Primary school not finished; 3=Primary school finished; 4=Secondary school not finished; 5=Secondary school finished; 6=High school not finished; 7=High school finished; 8=More advanced)[10]	305	5.256	1.405	1	8
Adults	Number of adults in a household	305	3.157	1.328	1	11
Kids	Number of kids in a household	300	1.043	1.107	0	4
Land tenure	Land tenure status (1=owned, 0=rent or borrow)	305	1.823	0.481	0	2
Income	Annual income of household in VND million	305	175.865	134.1851	0	1300
Household's farming activities						
Coffee production	Total coffee product harvested last crop year	305	3.017	2.094	0	16
Total area	Total farm area (ha)	305	1.289	1.075	0	10

[10] Education levels in Vietnam: Primary school is Years 1 to 5; Secondary school is Years 6 to 9; High school is Years 10 to 12. After that, students study a diploma or undergraduate degree at universities.

Table 2. *Continued*

Variable	Description	Obs	Mean	Std. Dev.	Min	Max
Coffee area	Total coffee area (ha)	305	1.019	0.681	0	7
Production loss	Number of time household experienced productivity loss during the last 10 years	304	2.036	1.674	0	10
Coffee trees from 1 to 8 years	Number of coffee tree under eight years old (prepare for harvest period)	292	346.825	514.714	0	3300
Coffee trees from 9 to 15 years	Number of coffee tree under 9–15 years old (peak productivity)	292	119.658	268.599	0	1600
Coffee trees from 16 to 20 years	Number of coffee tree under 16–20 years old (start decreasing the productivity)	289	164.464	338.305	0	2000
Coffee trees 21 years and older	Number of coffee tree 21 years old and older (very low productivity)	284	447.796	647.638	0	7000
Chemical fertilisers	Total amount of chemical fertiliser used (kg)	293	2.198	3.315	0.1	52
Organic fertilisers	Total amount of organic fertiliser used (kg)	251	3.906	6.155	0	40

Source: Author calculated from survey

6.2. Results of pairwise rankings data

Table 3 presents the aggregate (average) part-worth utilities attached to the five SAP attributes from the pairwise rankings DCE conducted using *1000minds*. The higher the weight, the stronger the preference farmers have for the attribute, and the weights sum to one. The largest three part-worth utilities are increase in profits, lower risk of output loss and increase in environmental benefits. The values for these three part-worth utilities are very similar, ranging from about 0.24 to 0.25. While this lends support to our hypothesis that profitability is central to the preference of farmers in adopting SAPS, risk of output loss and environmental benefits play an equal role. Coffee farmers have weaker preferences for the attributes relating to SAP set-up time and increased daily effort with part-worth utilities of about 0.15 and 0.11 respectively. These findings provide some clear messages to policymakers: SAPs that increase profits, benefit the environment and are unlikely to result in output loss are likely to be favoured by coffee farmers, even if they take time to establish and require additional daily work.

The dendrogram from Ward's linkage clustering approach is provided in Figure 3. It clearly suggests that the data should be grouped into three clusters. Summary statistics for clustering based on the Ward's linkage and *k*-means approaches are provided in Tables 4 and 5 respectively. The statistics are very similar across these two approaches, showing coffee farmers clustered into three groups. The first cluster has the strongest preference for profits, the second for lowered risk of output loss and the third for environmental benefits. These clusters are labelled accordingly as Profit, Risk and Environment.

Table 3: Preference values at aggregate level for the attributes with pairwise rankings data

Attribute	Mean part-worth utility (weight)
Increase in profits	0.251
Lower risk of output loss	0.250
Increase in environmental benefits	0.239
Lower time required to set up	0.148
Increase in daily effort	0.112

Figure 3: Dendrogram using Ward's clustering approach

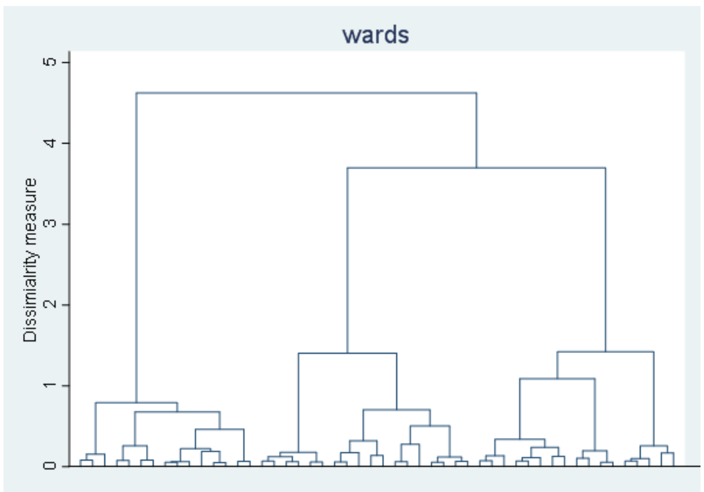


Table 4: Preference values for the attributes in each cluster using Ward's linkage clustering

	Cluster 1 (Profit)		Cluster 2 (Risk)		Cluster 3 (Environment)	
Variable	**Obs**	**Mean**	**Obs**	**Mean**	**Obs**	**Mean**
Increase in profits	91	0.35	82	0.14	132	0.26
Increase in environmental benefits	91	0.15	82	0.22	132	0.31
Increase in daily effort	91	0.11	82	0.15	132	0.09
Increase in risk of output loss	91	0.24	82	0.29	132	0.23
Increase in time required to set up	91	0.15	82	0.20	132	0.11

Table 5: Preference values for the attributes in each cluster using *k*-means clustering

	Cluster 1 (Profit)		Cluster 2 (Risk)		Cluster 3 (Environment)	
Variable	**Obs**	**Mean**	**Obs**	**Mean**	**Obs**	**Mean**
Increase in profits	109	0.35	85	0.15	111	0.23
Increase in environmental benefits	109	0.17	85	0.21	111	0.33
Increase in daily effort	109	0.09	85	0.16	111	0.09
Increase in risk of output loss	109	0.22	85	0.30	111	0.23
Increase in time required to set up	109	0.16	85	0.18	111	0.11

The clustered data were then analysed using multinominal logit models to examine which socioeconomic and demographic variables are associated with the participants in the three clusters. Results are provided in Table 6. Findings suggest that older farmers are more likely to belong to the Risk cluster and less likely to belong to the Environment cluster. Educated farmers are more likely to belong to the Profit cluster, while farmers who do not own their land or farm are less likely to belong to the Environment cluster. The coefficients on the district dummy variables indicate that, after controlling for these factors, farmers in Krong Pac value the environment more highly whereas those in Cu Kuin favour profits over the other attributes.

Table 6: Results of multinomial logit using Ward's linkage clustering data

	(1) Profit cluster	(2) Risk cluster	(3) Environment cluster
Age	-0.000957	0.00743**	-0.00647*
	(-0.39)	(3.16)	(-2.54)
Gender	0.0164	-0.0742	0.0578
	(0.30)	(-1.35)	(1.00)
Secondary education	0.122*	-0.0678	-0.0540
	(2.17)	(-1.27)	(-0.88)
Income	-0.00138	-0.0000341	0.00142
	(-1.67)	(-0.04)	(1.73)
Farm not owned	0.112	0.0937	-0.206*
	(1.53)	(1.29)	(-2.34)
Cu Kuin district	0.256**	-0.0427	-0.213*
	(2.89)	(-0.40)	(-2.05)
Cu Mgar district	0.0987	0.238**	-0.337***
	(1.24)	(3.29)	(-4.23)
Krong Nang district	0.0621	0.111	-0.173*
	(0.78)	(1.53)	(-2.24)
Krong Pac (omitted district)	-	-	-
N	294	294	294

Note: t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6.3. Results of stated preference data

Results from the stated preference data analysis for determinant attributes of SAP are presented in Table 7 whereas results of analysis with heterogeneity in farmers characteristics are presented in Table 8. The results show that there is heterogeneity in preference for attributes across coffee farmers (except for the increase in daily effort) as the coefficient associated with each attribute is significant in the GMNL analysis. After controlling for heterogeneity in the mean, we found associations between increased profits as well as increased environmental benefits with the preference for SAPs. The effects are positive and relatively large (with values of about 1.4 and 0.5

respectively). As expected, the coefficients of the attributes on daily effort, risk of output loss and time needed to set up are negative, which means that coffee farmers are less attracted to higher levels of labour-intensive, risky and time-intensive practices. The coefficient of the risk attribute is also relatively large with a value of around 1. These findings are similar to those from other studies (e.g., Kassie et al., 2015; Owusu Coffie et al., 2016) and are consistent with those from the pairwise rankings DCE discussed above. These results also confirm that heterogeneity is statistically significant across all attributes with the exception of daily effort, which lends support to using the GMNL approach.

Analysis of the data where farmers are allowed to opt for the status quo reveals that only three of the five attributes are statistically significant: profits, environmental benefits and the risk of output loss. Again, the coefficients of the first two attributes are positive, while the coefficient of the risk attribute is negative. However, the coefficients are smaller in magnitude than those from the forced choice DCE. Further, with the exception of the daily effort attribute, these results confirm the existence of statistically significant heterogeneity across the attributes. As stated in Oehlmann et al. (2017) those who observe the quality of the surrounding environment as high may be less likely to choose alternatives that prescribe improvements compared to the status quo. In the case of coffee farming, farmers still weight environmental benefits as an important attribute even when they have the opt out option. This signals that they do actually value more environmentally friendly practices. Policymakers should take this information into account.

The heterogeneity in farmers' preferences for SAPs is not only dependent on the unobserved attributes but also on their socioeconomic characteristics. This is why previous DCE analyses have included interaction terms between key attributes and demographic factors. In this study, we found age, education, income and tenure (experience in coffee cultivation) to play important roles in explaining the heterogeneity in farmers preferences for SAP adoption. The results are shown in Table 8. Most of the coefficients of the interaction terms are statistically insignificant but similar to the MNL results of the pairwise rankings data. The results suggest that older farmers are less likely to value the environmental attribute of a SAP and better educated ones are more likely to favour the profit attribute. There is also evidence that farmers with higher incomes are more likely to value the environmental attribute.

Table 7: Results of GMNL model for forced choice and choice with status quo

VARIABLES	Forced choice analysis	Choice with status quo analysis
Taste parameters		
Increase in profits	1.368***	1.149***
	(0.141)	(0.088)
Increase in environmental benefits	0.465***	0.151***
	(0.078)	(0.056)
Increase in daily effort	-0.247***	0.01
	(0.061)	(0.047)
Increase in risk of output loss	-0.978***	-0.665***
	(0.108)	(0.061)
Increase in time required to set up	-0.170***	-0.064
	(0.061)	(0.056)
Heterogeneity in mean		
inc_profit	0.986***	0.895***
	(0.123)	(0.080)
inc_environment	0.602***	0.523***
	(0.114)	(0.077)
inc_effort	0.229	0.132
	(0.151)	(0.167)
inc_risk	0.443***	0.330***
	(0.117)	(0.090)
inc_time	0.639***	0.648***
	(0.085)	(0.070)
Tau	-0.427**	0.283
	(0.201)	(0.263)
Gamma	0.435	0.353
	(0.433)	(0.781)
N of obs	6,076	9,114
Degree of freedom	12	12
LL	-1642	-2789
AIC	3307.599	5601.764
BIC	3388.144	5687.174

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Results of the GMNL model with observed heterogeneity

Variables	Full GMNL - orced choice		Full GMNL - choice with status quo	
	coeff.	**SE**	**coeff.**	**SE**
Taste parameters				
Increase in profit	1.135***	(0.340)	0.746***	(0.270)
Increase in environmental benefits	0.416	(0.255)	0.046	(0.204)
Increase in daily effort	-0.652***	(0.222)	-0.260	(0.175)
Increase in risk	-1.223***	(0.292)	-0.670***	(0.200)
Increase in time	-0.063	(0.221)	-0.073	(0.217)
Heterogeneity in mean				
ASCs				
Increase in profit	0.931***	(0.105)	0.834***	(0.081)
Increase in environmental benefits	0.512***	(0.118)	0.467***	(0.081)
Increase in daily effort	-0.224	(0.142)	-0.096	(0.186)
Increase in risk	-0.423***	(0.108)	0.329***	(0.091)
Increase in time	0.610***	(0.081)	0.629***	(0.068)
Observed heterogeneity				
profit*age	-0.008	(0.006)	-0.001	(0.005)
envir*age	-0.010**	(0.005)	-0.005	(0.004)
effort*age	0.007*	(0.004)	0.002	(0.003)
risk*age	0.006	(0.005)	-0.003	(0.004)
time*age	0.000	(0.004)	-0.001	(0.004)
profit*gender	0.135	(0.171)	0.225	(0.143)
envir*gender	0.071	(0.136)	0.022	(0.111)
effort*gender	0.009	(0.113)	0.042	(0.095)
risk*gender	-0.061	(0.138)	-0.075	(0.103)
time*gender	-0.009	(0.118)	0.017	(0.115)
profit*educ	0.377**	(0.173)	0.440***	(0.145)
envir*educ	0.069	(0.138)	0.095	(0.112)
effort*educ	0.039	(0.117)	0.123	(0.097)
risk*educ	-0.003	(0.143)	0.029	(0.108)
time*educ	0.153	(0.122)	0.300**	(0.119)
profit*inc	0.006**	(0.002)	0.001	(0.002)
envir*inc	0.008***	(0.002)	0.005***	(0.002)

Table 8. *continued*

Variables	Full GMNL - forced choice		Full GMNL - choice with status quo	
	coeff.	SE	coeff.	SE
effort*inc	0.002	(0.002)	0.002	(0.001)
risk*inc	-0.000	(0.002)	0.003*	(0.001)
time*inc	-0.004**	(0.002)	-0.003*	(0.002)
profit*tenure	-0.208	(0.240)	-0.081	(0.203)
envir*tenure	0.162	(0.197)	0.284*	(0.160)
effort*tenure	-0.057	(0.162)	-0.085	(0.136)
risk*tenure	0.238	(0.191)	0.120	(0.146)
time*tenure	-0.248	(0.175)	-0.088	(0.168)
Tau	0.355*	(0.198)	0.264	(0.267)
Gamma	0.456	(0.488)	0.764	(0.830)
N	6,056		9,084	
Degree of freedom	30		30	
LL function	-1612		-2754	
AIC	3298.542		5581.944	
BIC	3546.768		5845.172	

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

6.4. Willingness to pay estimates

The profit attribute in the DCEs is a monetary attribute which can be used to calculate a WTP. Below we calculate the WTP for each attribute under the two DCE approaches.

6.4.1. WTP under pairwise rankings approach

The WTP is the number of currency units (i.e., VND) that each part-worth utility unit is worth. The mean part-worth utilities for each attribute and the corresponding WTP are presented in Table 9. We can see that an increase in profits from low to high is equivalent to an increase of VND 70 million[11] (from VND 10 million to VND 80 million) per hectare per year. Therefore, each

[11] In December 2017, 1USD = 22,699 VND; 1AUD = 17,721 VND.

unit of utility is valued at VND 2.8 million (70/25). This price per unit allows us to convert the part-worth utilities associated with the non-monetary attributes into a WTP. These are shown in the final column of Table 9. For example, coffee farmers are willing to pay almost VND 67 million per hectare per year to increase environmental benefits from low to high. In terms of risk, they are willing to pay nearly VND 70 million to reduce the risk of losing output from high to low for one hectare of farm per year. Smaller values of WTP are found for the daily effort and set-up time attributes.

Table 9: Willingness to pay calculation for pairwise rankings data

Attribute	Mean	WTP (mil. VND)
Increase in profits		
Low (10 million VND/ha/year)	0%	-
Medium (45 million VND/ha/year)	15.6%	-
High (80 million VND/ha/year)	25.0%	-
Increase in environmental benefits		
Low	0%	
Medium	13.4%	37.52
High	23.9%	66.92
Increase in daily effort required		
High	0%	
Medium	6.7%	18.76
Low	11.4%	31.92
Increase in risk (of output loss)		
High	0%	
Medium	15.2%	42.56
Low	24.7%	69.16
Increase in time required to set up		
Long (>2 years)	0%	
Medium (1–2 years)	8.2%	22.96
Short (<1 year)	14.9%	41.72

6.4.2. WTP under stated preference approach

With choice set data, WTP estimates equate to the marginal rate of substitution between the (statistically significant) attributes and their prices. Specifically, the monetary value of the implicit price of non-monetary attributes is calculated using equation (7) and summarised in Table 10. The ratio of the coefficient on each non-monetary attribute and profit is multiplied by VND 45 million which is the gap between increasing profits from low to medium and from medium to high.

$$WTP_j = -\frac{\beta_j}{\beta_{profit}} * 45 \text{ million VND} \qquad (7)$$

Using the coefficient estimates from the preferred GMNL models identified above, the WTP is highest for minimising the risk of output loss. Coffee farmers in Vietnam are willing to pay (on average) between VND 26 million (if they still can choose the status quo) and 32 million (if they must change their farming practice) for a one level reduction in risk of output loss (i.e., from high to medium or from medium to low). For environmental benefits, the negative sign on the WTP estimates implies that farmers are willing to accept VND 15 million less in profits to achieve a one level increase in environmental benefits. For the choice set data with a status quo option, no estimates for the WTP are provided for the daily effort and time attributes since the coefficients attached to these attributes were not statistically significant.

The values of WTP are lower for the stated preference data compared to the pairwise rankings data. Due to using different algorithms in generating choice sets, the WTP results from the two datasets are not similar in terms of the magnitude. However, both WTP calculations confirm that Vietnamese coffee farmers are willing to pay a positive value for reducing the risk of output loss, the time required to set up and the effort needed to manage a new SAP, while they are willing to sacrifice net profits to obtain a higher level of environmental benefits.

Table 10: Willingness to pay for non-monetary attributes

Attribute	WTP using GMNL for forced choice (mil. VND)	WTP using G-MNL for choice with status quo (mil. VND)
Increase in environmental benefits	-15.30	-5.91
Reduced daily effort required	8.125	-
Reduced risk (of output loss)	32.47	26.04
Reduced time to set up	5.60	-

Note: The WTPs are calculated based on coefficient estimates from Models (1) and (4) in Tables 5 and 6, respectively.

7. Conclusion and Policy Implications

Traditional coffee farming techniques in Vietnam are placing considerable strain on the environment. Many farmers have also reported recent falls in productivity. Adopting SAPs can minimise environmental impacts, increase productivity as well as improve the quality of the coffee beans in the long term (The sustainable trade initiative - IDH, 2019). In recent years, large amounts of financial resources have been directed towards the coffee sector in Vietnam. In 2017, the Vietnamese government adopted programs aimed at producing high-quality coffee and invested USD $7.3 million in sustainable coffee production schemes [12]. The World Bank has also invested considerable amounts in transforming the coffee sector in Vietnam since 2016 (via Sustainable Agriculture Transformation project), yet the uptake of SAPs has not lived up to expectations.

[12] See decision number 787/QD-TTg here: http://vanban.chinhphu.vn/portal/page/portal/chinhphu/hethongvanban?class_id=2&_page=1&mode=detail&document_id=189978.

For the promotion of SAPs to effectively lead to adoption, programs should be designed based on farmer preferences rather than devised from a technician or policymaker perspective. This study provides empirical evidence on the intrinsic attributes of SAPs that coffee farmers in Vietnam value most. Two different DCEs were conducted and analysed to discern such preferences. This is the first study using two different DCE approaches to take advantage of the benefits of each approach and compare the results. Findings from both approaches suggest that coffee farmers in Vietnam value profits, lower output loss risk and environmental benefits over the time it takes to establish SAPs and the increase in daily effort required to manage them. In addition, the results of DCEs were used to calculate the WTP of coffee farmers in Vietnam for non-monetary SAP attributes (i.e., environmental benefits, risk of output loss, time required to set up and effort required to manage SAPs).

While estimates of WTP vary across the DCE approaches, it is clear that coffee farmers in Vietnam are willing to forgo profits for the sake of environmental benefits. Given the value that coffee farmers assign to the environmental benefits of their production techniques, policymakers should feel optimistic that programs encouraging SAP adoption among coffee farmers in Vietnam and elsewhere will be successful. However, in doing so, they must be able to demonstrate that profits will not fall, otherwise they are likely to be met with resistance. Moreover, given the importance farmers place on the risk of losing output, SAPs must demonstrate that production is as reliable as using traditional techniques and that coffee trees are not vulnerable to the impact of climatic factors such as drought and flooding. Schemes must also be widely available to coffee farmers that allow them to insure against the risks they face relating to the loss of crops. Finally, when devising SAPs, policymakers should be aware that preferences vary across farmer groups. Findings from cluster analysis reveal that older farmers have a stronger preference for reduced risk and a weaker preference for environmental benefits. Higher educated farmers have a higher preference for profitability. These lessons should be applied to the design and targeting of SAPs in Vietnam and other similar countries.

Based on characteristics of some SAPs already available in the market and the findings from this study, it is possible to speculate which of these are more likely to be adopted if promoted. For example, while the rejuvenation of coffee trees is likely to lead to a large increase in profits, it is also associated with a high level of risk and therefore unlikely to appeal. While the increase in profits from adopting drip and sprinkler irrigation systems is deemed to be low, these approaches are associated with a low level of risk and high environmental benefits. Soil and/or leaves testing is another low-cost SAP that farmers are likely to adopt given its environmental benefits, although the expected increase in profits from this practice is low.

The research is not without its limitations. While none of the farmers that participated in the research were adopting SAPs, we did not control for differences in their existing coffee production techniques. Future research could collect and examine this type of information. Further, our SAPs were hypothetical in nature and it would be useful to examine different adoptions rates for actual SAPs and why they differ. Future research could also compare stated preference data with revealed preference data and examine the actual impact of SAPs that farmers adopt under different circumstances. Larger sample sizes of farmers could also enhance DCE findings.

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