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A choice experiment approach to evaluate maize farmers' decision-making processes in Lao PDR

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ABSTRACT

Sustainable intensification seeks to increase outputs from existing farmland in ways that have a lower environmental impact. An extensive literature has examined the determinants of farmers' adoption of the different agro-ecological cropping systems needed to achieve these goals. However, the farmers' preferences for the attributes of these systems and the decision processes for choosing between available systems is still poorly understood. To fill this gap, this paper proposes a methodology that relies on a discrete choice experiment to analyse farmers' preferences for cropping systems and estimate the heterogeneity of decision processes among farmers. We modelled three major types of decision processes potentially used by farmers to evaluate the systems that are not consistent with the standard utility maximization framework. These findings offer insights into the behavioural patterns of respondents and should help crop system promoters and developers to better understand how their proposed systems are likely to be evaluated by different types of farmers.

1. Introduction

The goal of agricultural sustainable intensification is to increase food production from existing farmland in ways that safeguard its productive capacity and have a lower environmental impact (Garnett et al., 2013). Ideally, sustainable intensification should also increase contributions to natural capital and the flow of environmental services (Pretty, 2014). Many agro-ecological cropping systems[1] promoted in recent decades, such as intercropping, improved fallow, crop rotation, conservation tillage, could play a significant role in achieving these goals. Despite efforts to promote the apparent benefits for farmers, the adoption of these agro-ecological systems remains low in the tropical world, especially in South-East Asia (Kassam et al., 2015). Although several studies have looked into the challenges to broad adoption (e.g., Knowler and Bradshaw, 2007), the reasons for the low adoption rates are still not

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[1] The term "cropping system" refer to the crops, crop sequences and management techniques used on a particular agricultural field.

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fully understood.

This paper tests farmers' preferences for different aspects/attributes of cropping systems. We develop a discrete choice experiment (DCE) where farmers are asked to compare and choose between cropping systems that have contrasted impacts on the farm resources and organization. The use of DCE is becoming increasingly popular to evaluate the potential choices to be made by farmers (e.g., Blazy et al., 2011; Useche et al., 2013; Ortega et al., 2016). To add to that literature, we explore the possibility that the decision-making process used in making a choice may in fact vary across farmers. This issue has received some attention in marketing and health economics (Gilbride and Allenby, 2006; Erdem et al., 2014). However, while the technology adoption literature have already used DCE to analyse preferences over alternative agricultural technologies or alternative cropping systems, to the best of our knowledge, most studies ignored the possibilities that farmers may not conform to the standard utility hypotheses used when responding to DCEs. Among the exceptions, Rodríguez-Entrena et al. (2019) who studied the presence of Attribute Non Attendance (ANA) for farmers choosing among agri-environmental schemes, and Owusu et al. (2021) who studied ANA for farmers choosing insurance contracts. However, to the best of our knowledge, this is the first study to assess the possibility of other heuristics such as Elimination by Aspects (Tversky, 1972) in agriculture.

2. Detecting farmers decision-process

DCEs can capture otherwise hard-to-measure components of farmers' decisions. They became an increasingly important tool used to study preferences and discuss farmers' potential behaviour when proposed new cropping systems, or new contracts (Birol et al., 2009; Duke et al., 2012; Useche et al., 2013; Jaeck and Lifran, 2014; Knowler, 2015; Ortega et al., 2016; Owusu, 2018; Dam et al., 2021; Owusu et al., 2021). A DCE is based on standard economic theory and assumes that the decision maker is a rational utility maximizing agent who will choose the alternative that provides him or her with the highest utility. Standard DCE also assumes that the decision maker is willing and able to make trade-offs between the desirable and undesirable aspects of each alternative. Finally, DCE assumes that respondents consider all aspects or attributes of the alternatives in the same manner. However, there is mounting evidence that people use a wide range of simplifying strategies which are inconsistent with these assumptions (Hensher et al., 2005; Scarpa et al., 2009; Hensher, 2014a, 2014b; Erdem et al., 2015; Sandorf et al., 2017).

Two simplifying strategies have been particularly studied. Firstly, the Elimination-By-Aspects (EBA) strategy which emerges when the decision maker eliminates any alternative that either includes an undesirable *aspect*[2] or does not include a desirable one from the choice set (see e.g. Batley and Daly, 2006; Erdem et al., 2014; Hess et al., 2012; Tversky, 1972). Secondly, the Attribute Non-Attendance (ANA) strategy which emerges when the decision maker is considering only a subset of the attributes describing the alternatives, thus ignoring one or more attributes (Scarpa et al., 2009, 2013; Hensher et al., 2012; Hensher, 2014a). The EBA and ANA correspond to non-compensatory behaviours: in the case of EBA, the decision maker will not accept any compensation for the undesirable *aspect* present in the choice set; in the case of ANA the respondent will not consider some of the trade-offs. Both decision-making processes could be present when farmers choose between cropping systems.

These simplifying strategies can, to some degree, be detected by asking the decision makers directly how they made their choices, e.g. stated ANA (Alemu et al., 2013; Scarpa et al., 2013). The presence of these strategies can also be inferred from the choices observed. For EBA, recent examples of this last approach include the work of Erdem et al. (2014) and Daniel et al. (2018). For ANA, examples of this approach include Hess and Hensher (2010), Scarpa et al. (2013), Hole et al. (2014) and Thiene et al. (2015).

Even if cropping systems create favourable outcomes such as increased yields, farmers might employ EBA rules if it requires large investments or if it leads to degraded soils in the long term. If some farmers do not want to make trade-offs with respect to such attributes but simply exclude alternatives from the choice set that contains either of them, this indicates that adoption depends crucially on how these two aspects are formulated and implemented. Hence, failing to consider the actual decision-making process might lead to wrong inferences with respect to adoption potential, and hence the applicability of the results for prediction and policy recommendation can be limited.

To test whether farmers employ such decision-making processes, we used a survey to collect DCE data in Lao PDR and analysed these through an equality constraint latent class model[3] (Scarpa et al., 2009) in order to detect EBA and ANA heuristics from the stated choices. Our model builds on the formulation of EBA found in Erdem et al. (2014) and Daniel et al. (2018) and the formulation of ANA using an inferred attribute non-attendance model proposed by Scarpa et al. (2013). To avoid selecting the ANA classes in an arbitrary manner, we used the modelling approach proposed by Vij and Krueger (2017) to identify the attributes that were non-attended by a significant proportion of the sample.

To the best of our knowledge, our approach represents the first attempt to jointly detect the presence of EBA and ANA strategies in DCE evaluating agricultural systems.

3. Context and study area

The rapid changes that have occurred in the mountainous areas of Southeast Asia provide a case for studying sustainable intensification. Improving infrastructures and increasing demand for animal feeds have transformed subsistence farming systems based on

[2] An aspect can be understood as the particular level taken by a particular attribute.

[3] The Equality constraint latent class model was first used by Scarpa et al. (2009) to detect the presence of ANA. In their model, different classes of ANA are tested but the parameters, that are allowed to be non-zero, are kept equal across the different ANA classes.

slash-and-burn rice production into market-connected systems heavily dependent on the continuous cropping of hybrid maize (Castella et al., 2012; Vongvisouk et al., 2016). However, this agricultural transition is also expected to increase the negative environmental impacts of farming systems (Valentin et al., 2008). Nowadays, maize mono-cropping profitability is decreasing because of poor agronomic performance (Lairez et al., 2018), itself probably resulting from a decrease in the quality of the supporting and regulating services of the ecosystem. In addition, farm incomes are more uncertain when based on a single source of revenue.

These sustainability issues can be addressed with some adaptations to the existing maize cropping systems. Possible adaptations include 1) better management of soil fertility and weeds with intercropping/rotation of maize with a legume crop, 2) reducing runoff and leaching by direct seeding in straw mulch combined with a cover, 3) increasing resource use efficiency by intercropped maize with crops that are able to extract the leached nitrogen under the root front of maize during their coexistence and then return it for the next cycle. However, these modified maize cropping systems may initially reduce the income or make it more uncertain or, increase the workload of the farm household (e.g., Affholder et al., 2010). Other possible adaptations include improved pasture or fruit trees. Like the maize-based systems, these adaptations can lead to an increase in workload or in the case of improved pasture a decrease in annual cash out needed but a longer period before getting a return on investment.

The data used in this study is from a farm household survey conducted in the province of Xieng Khouang located in northern Lao PDR. The province is typical of the land use changes that occurred in Southeast Asia in the 2000s. Hybrid maize cultivation replaced traditional upland rice, gardens, orchards and also expanded into forests and fallow areas (Castella et al., 2012).

We selected the Kham district because it was representative of the agricultural intensification and its consequences in the Xieng Khouang province. Kham district has a good road network making it easily accessible (Andersson et al., 2007). A typical farm produces hybrid maize on the uplands (1–3 ha), lowland paddy rice mainly for household consumption (1–3ha; 1 cycle per year from June to October), and grows dry season vegetables (garlic, onions, watermelon, cucumber; around 0.1ha) on the lowlands from December to April. Many households have developed a weaving activity for their daily expenditure. Some farms also raise cattle in an extensive way: free roaming during the dry season and a natural grass cut-and-carry system during the cultivation period.

4. Empirical work

We developed a DCE aimed at understanding the trade-offs that farmers were willing to make when having to choose between contrasted cropping systems. We first describe the construction of the DCE that required a careful definition of the systems attributes that farmers may consider when making choices, and then the construction of an experimental design to propose choice scenarios of these systems to selected farmers. We then describe the modelling framework aimed at detecting the presence of the different decision processes.

4.1. Design of the choice experiment

4.1.1. Elicitation of attributes

The list of attributes and levels used in the DCE is presented in Table 1. This list is the result of an iterative process that involved the review of recent literature, focus group discussions with farmers conducted in three villages of the Kham district, and consultations with agronomists who had working experience in the study area. Jourdain et al. (2020) provide a detailed description of this process and further discuss the attributes and levels selected for this study.

Examples of cropping systems that could be considered by farmers in the study area, and their effects on the selected attributes are presented in Table 2. They show that farmers could relate the combination of attributes to realistic cropping systems, which was an important criterion for the validity of the experiment (Johnston et al., 2017).

4.1.2. Experimental design

The five attributes and their levels gave rise to $5^3 = 125$ possible scenarios in a full factorial design. We first conducted a pre-survey with 10 farmers using an orthogonal design with 18 choice sets. Each of the three alternatives was described using the five attributes specified in the previous section.

We estimated a conditional logit model, and used the estimated parameters to optimize a D-efficient design with 18 choice tasks using Ngene v.1.1.2 (Rose and Bliemer, 2009). We split the sets into three blocks of six choice tasks each. To avoid unrealistic scenarios, we included a constraint for the generation of the sets that rejected scenarios of high income and low maximum economic loss, or low income and high maximum economic loss. The D-error of the final experimental design was 0.0203. Each respondent was provided

Table 1
Choice attributes and levels.

Attribute	Description	Levels[a]
Income	Average market value of crop products (yield x price)	80%, *100%* and 150% of the current income
Labour	Average labour requirements of the cropping system	80%, *100%* and 150% of the labour requirement
Cash Outflow	Average cash requirements of the cropping system	80%, *100%* and 150% of the cash requirement
Max Eco. Loss	Maximum economic loss of income without considering the likelihood of its occurrence	200, *400*, and 2,000 thousand Kip/ha
Soil fertility	Impact on soil fertility	Increase/*Identical*/Decrease

[a] Current situation in italics.

Table 2
Examples of alternative cropping systems[a] and their corresponding attributes.

	Crop rotation maize-soybean	Conventional tillage, maize intercropping with rice bean	Direct seeding mulch-based cropping systems	Direct seeding/No Rotation/ No Mulch
Income	++	+	+	0
Labour	++	+	++	–
Cash Outflow	0	0	–	+
Max Eco. Loss	+	+	–	++
Soil fertility	+	+	++	–

[b] "++", "+", 0, "-" represent expected effects of the alternative systems on the different attributes as summarized from personal interviews with agronomists who had working experience in the study area.
[a] The current system corresponds to maize mono-cropping, with low fertilizer use. The zero means they are considered as the base level.

with one of the blocks, and we randomized the order of the choice sets presented to each respondent. Each choice set included two unlabelled alternatives and a status quo (See Annex A for a full description of the survey and example of choice set).

4.1.3. Survey methods

From May to July 2017, we conducted 120 face-to-face interviews with farmers from six villages of the Kham district (Dokham, Laeng, Le, Houat, Xay and Nadou), which contrasted in terms of their ecological zone, road accessibility and village size. To select farmers we used the information available from previous household surveys conducted in these villages (EFICAS, 2017) and a cluster analysis that characterized the diversity of farmers based on the household head's age, the household size, the rice and maize cropping areas, the number of cattle's head and other assets that suggested the presence of three homogeneous types of farmers. We chose farmers evenly in each cluster. If the pre-selected farmers were not present or available when the team visited the village, they were replaced with substitutes of the same cluster. Farmers were asked to confirm their consent to participate in the survey after being informed about the objectives and process of the survey, but no farmers declined to participate at that stage.[4] The interviews were conducted in the farmers' homes. Questions were addressed directly to the household head (identified as the person responsible for providing for the most daily expenditures) or to the 'second in command' household member 20 years of age or older living on the premises.

To minimize the differences in information or interpretation among the respondents, the interviewers explained the concepts and purposes of the survey, presented an overview of the different attributes to be compared using pictorial cards and brief descriptions along with the terms, discussed the attributes until reaching an agreement on the meaning of the attributes and levels presented. To minimize possible biases introduced by having several interviewing styles, all interviews were conducted by the third author and a unique interpreter. We emphasized that responses would remain anonymous to minimize the social desirability bias. No incentives were given to stimulate participation.

4.1.4. Data analysis and models

We tested the possibility that respondents had non-compensatory modes of decision when choosing their cropping systems. In addition to the standard random utility model (RUM) (McFadden, 1974), we included two possible decision-making processes. Some farmers might ignore some of the attributes (corresponding to ANA), while some others might use an EBA decision-making process. We directly inferred the presence of these decision-making processes by estimating analytical models based on the latent class choice modelling framework, where, in addition to allowing for differences in the utility parameters across classes, we allowed for differences in decision-making process that was used (as, for example, in Hess et al., 2012).

We observed $N = 120$ decisions makers, each making $T = 6$ separate choices. We assume that the respondent n used a decision-making process m characterized by a vector of parameters β_m. Let $P(y_n|m)$ the probability of observing the sequence of choices $y_n = [i_{n1}, i_{n2}, \dots, i_{nT}]$ made by respondent n conditional on n using the decision-making process m. We make the hypothesis that M decision-making processes are present in the data set, each based on its own vector of parameters and model structure. Since the choice of decision rule for a given respondent is not observed, it is treated as a latent component. The probability for the sequence of choices observed for respondent n becomes:

$$P(y_n) = \sum_{m=1}^{M} \pi_{n,m} P(y_n|m) \; where \; \sum_{m=1}^{M} \pi_{n,m} = 1 and \pi_m \in [0,1] \tag{1}$$

We investigated the presence of three decision-making processes.

The first decision process corresponded to a full attendance, full-compensatory strategy and was modelled with the standard RUM.

[4] This procedure results from the way respondents are usually recruited in rural communities in Southeast Asia. Farmers can only be invited to participate through the village chief. Under these conditions, it was probably more difficult for farmers to refuse directly to participate in the survey. One possible strategy for farmers was to declare their unavailability. It is therefore difficult to distinguish between refusal to participate and actual unavailability, and we have not reported the percentage of refusals to participate.

The utility of the alternative *i* for respondent *n* in the choice situation *t* was represented as: $U_{nit} = \beta' X_{nit} + \varepsilon_{nit}$, where X_{nit} is a vector of K observed attributes, β' is a vector of preference parameters; ε_{nit} is the unobserved error term assumed to be distributed as *iid* Type-I extreme value distributions with a constant variance of $\pi^2/6$ (McFadden, 1974). It allowed the estimation of the marginal utility coefficients based on the assumption that respondents (a) consider all alternatives and attributes in a compensatory manner; (b) maximize their utility. The probability of observing a sequence y conditional on β is (Louviere et al., 2000):

$$P(y|\beta, RUM) = \prod_{t=1}^{T} \frac{\exp(\beta'.X_{nit})}{\sum_{j=1}^{J} \exp(\beta'.X_{njt})} \tag{2}$$

The second decision process tested is a special form of elimination by aspects. In its pure form, EBA is a simplifying strategy where people sequentially eliminate alternatives from their choice set based on the level of one or a few attributes until a single alternative remains (Tversky, 1972). It supposes a complete order and ranking of attributes and levels. As this poses estimation issues, a hybrid decision strategy was evaluated assuming that a respondent start by eliminating undesirable alternatives from their choice set to form a smaller consideration set, and then choose between the remaining alternatives in a compensatory manner (Swait, 2001; Gilbride and Allenby, 2006). The same approach is taken by several researchers in marketing (Gilbride and Allenby, 2004; Gilbride et al., 2006; Laurent, 2007), health (Erdem et al., 2014), and energy contracts (Daniel et al., 2018).

If the respondent eliminates one alternative based on an EBA rule, then the probability of choosing that alternative should be zero, and the choice probabilities are allocated across the remaining two alternatives. Hence, following Erdem et al. (2014) and Daniel et al. (2018), we develop a two-stage model where the first stage is described by an EBA process based on one attribute and the second stage a compensatory RUM process among the remaining choices. In fact, the model integrates both stages simultaneously. For a given EBA model formulation, the probability to observe one sequence of choice by a farmer becomes:

$$P(y_n|\beta, EBA_q) = \prod_{t=1}^{T} \frac{\exp(\beta'.X_{nit}).\left(1 - I_{x_{knit|q}}\right)}{\sum_{j=1}^{J} \exp(\beta'.X_{njt}).\left(1 - I_{x_{knjt|q}}\right)} \tag{3}$$

where $I_{x_{knit|q}}$ is an indicator function taking a value of 1 if the attribute level restriction as given by the EBA decision rule q is present in the alternative *i*. This approach restricts the probability of alternatives that are eliminated to zero and ensures that the EBA decision rule holds for the entire sequence of choices.

With five attributes describing the cropping systems, each having three levels, it would be possible to envisage many combinations of EBA decision rules. However, we only look at a subset of five rules each concerning only one attribute. Each EBA class corresponds to a rule discarding the alternative containing the highest absolute level of that attribute. The rule EBA-income eliminates the alternatives where benefits would decrease by 20%; EBA-labour eliminates the options where the labour requirement would increase by 50%; EBA-cash outflow eliminates the options where the cash outflows would increase by 50%; EBA-maximum economic loss eliminates the options where the maximum economic loss would be 2 million LAK; EBA-lower fertility eliminates the options where the soil fertility would decrease.

For the ANA model, the most popular latent class model to infer ANA patterns in the data is the equality-constrained latent class model (Campbell et al., 2011; Jourdain and Vivithkeyoonvong, 2017; Caputo et al., 2018). The ANA classes are pre-defined as different combinations of attendance and non-attendance across attributes. For each attribute, there exists a non-zero coefficient used in the attendance classes, while the coefficient is set to zero in the non-attendance classes (Hensher and Greene, 2010). The probability of observing a sequence y, assuming a preference vector β, and the ANA rule a is given by (Hensher et al., 2012):

$$P(y_n|\beta, ANA_a) = \prod_{t=1}^{T} \frac{\exp((\beta \circ \beta_a)'.X_{nit})}{\sum_{j=1}^{J} \exp((\beta \circ \beta_a)'.X_{njt})} \tag{4}$$

where β_a is a K-vector with zeros for non-attended attributes and ones for attended ones, and the function $\circ$ represents the element-to-element vector multiplication. When all possible combinations of non-attendance are considered, this becomes a latent class model with 2^k predefined classes. This leads to a large number of classes to be estimated and potentially unstable results. Different strategies have been employed to reduce the number of classes to be estimated: arbitrary limit the investigation to classes with one or two attributes simultaneously ignored (e.g., Scarpa et al., 2009; Thiene et al., 2015), ad-hoc reasoning about prior-plausibility of some ANA patterns to reduce the set of possible ANA classes, or an iterative procedure to eliminate non-plausible ANA patterns (Lagarde, 2013; Jourdain and Vivithkeyoonvong, 2017). None of these options are completely satisfactory, as they do not address the difficulty to disentangle ANA from low preferences for the attributes and contain a certain degree of arbitrariness (see Hess and Hensher, 2013). In order to choose, in a non-arbitrary way, the ANA classes to be estimated, and to discriminate between low-preference and ANA, we first analysed the data using the recently proposed mixed logit model with multivariate nonparametric finite mixture distributions developed by Vij and Krueger (2017). This model allows for a non-parametric representation of the distribution of preference parameters. To do so, the model decomposes the parameter space into a set of points distributed over a high-dimensional grid and estimates the probability mass of the parameter of each of these points. The location of each point on the grid is determined endogenously by the model. The model can approximate any multivariate probability distribution function to any arbitrary degree of accuracy. Vij and Krueger (2017) showed that their model allowed endogenously recovering of ANA patterns. When applied to our data, it also allowed us to limit convincingly the number of ANA classes to three.

In addition to heterogeneity in decision processes, we also wanted to test whether preferences for attributes were heterogeneous. Feeding the different model formulations into Equation (1), and leaving the possibility of P preferences classes, we obtain:

$$P(y_n) = \sum_{p=1}^{P}\left[\pi_{1,p}.P\left(y\middle|\beta_p, RUM_p\right) + \sum_{a=1}^{3}\pi_{m,p}.P\left(y\middle|\beta_p, ANA_a\right) + \sum_{e=1}^{2}\pi_{m,p}.P\left(y\middle|\beta_p, EBA_e\right)\right] \tag{5}$$

The actual decision process used by any given farmer is unobservable, but we can estimate the use of each of the six processes up to a probability using a latent class formulation (Greene and Hensher, 2003) where each class represents a combination of preference and decision-process. The probability for a farmer to belong to a preference class p and follow the process rule m is estimated using a multinomial logit model:

$$\pi_{m,p} = \frac{\exp\left(\theta_{m,p}\right)}{\sum_{p=1}^{P}\sum_{m=1}^{M}\exp\left(\theta_{m,p}\right)} \tag{6}$$

where θ_q is a constant corresponding to class of farmers that adopted the rule q. One class constant is set to zero for the identification of the model. We used the estimated $\widehat{\theta}$ to calculate the prior probabilities of each class as $\widehat{\pi}_{m,p} = \frac{\exp(\widehat{\theta}_{m,p})}{\sum_{p=1}^{P}\sum_{m=1}^{M}\exp(\widehat{\theta}_{m,p})}$; The standard error of each probability classes were estimated using the Delta method. We also applied the Bayes' formula to calculate the posterior estimates of the individual-specific class probabilities and then calculate their means and standard deviation (Greene and Hensher, 2003; Lagarde, 2013).

For the present paper, all models were coded and estimated using Julia (Bezanson et al., 2017) and the Optim package (Mogensen et al., 2018) for finding maximizers of the log-likelihood function. To deal with the issue of local optima, we conducted 50 estimation runs of our models with 50 different random sets of starting parameters for each model estimated. We then chose the initial parameters leading to the best likelihood.

5. Results and discussion

5.1. *The conditional logit model (CL)*

Firstly, as a basis for later comparison, we estimated parameters using a CL model. The results are presented in Table 3. All the coefficients are significantly different from zero and of the expected signs. This indicates that the attributes used for the experiment were relevant and important to farmers. The coefficient of the *no-change* option was negative, suggesting that farmers increased their utility when choosing one of the presented systems/practices compared to when choosing the *no-change* option and disutility aspects of the no-change option that was not described by the attributes. Increases in the expected income and soil fertility had a positive effect on the farmers' utility. Increases in the labour and cash requirements, the possibility of high revenue losses, or decreases of soil fertility, all had a negative effect on utility.

The results of an alternative model formulation with non-linear preferences for the income labour, cash outflow and maximum economic losses are presented in Annex B. The results suggest that preferences for these attributes may not be linear. These non-linearities could be the outcome of different marginal utility coefficients for increasing or decreasing requirements for cash or maximum economic losses. However, the non-linearities could also be a result of the ANA and EBA heuristics, which we will test in the subsequent sections.

Table 3
Conditional logit coefficient estimates.

Attribute	Coefficient[a]	St. Error	Sig[††]
No change (Status Quo)	−0.416	0.113	***
Income	0.156	0.030	***
Labour	−0.137	0.036	***
Cash outflow	−0.104	0.045	**
Maximum Economic Loss	−0.559	0.074	***
Lower Fertility	−2.605	0.282	***
Higher Fertility	1.773	0.137	***
Log Likelihood (LL)	−581.91		
LL (constants only)	−773.86		
AIC	1177.82		
BIC	1209.87		
D-error	0.0025		

[††] ***, **, * indicates significance at 1%, 5%, 10% level.

[a] For better convergence of the subsequent models, the attributes have been scaled. The attributes for Income, Labour, Cash outflows have been divided by 10, and the Maximum Economic Loss has been divided by 1,000,000. The fertility attribute has been effect coded.

5.2. Selection of ANA and EBA processes

We identified the ANA processes using the mixed logit with unequal grid model developed by Vij and Krueger (2017). This intermediary step was only used to screen-out the ANA decision-process not present in the data. For the sake of space, we moved the detailed presentation of the procedures and results of this step in Annex C. The results suggested that ANA was used as a decision rule with respect to the two attributes *cash outflow* and *maximum economic loss,* with 58% and 18% of the sample population likely insensitive to those attributes. It also suggested that around 12% of the sample population ignored simultaneously the *cash outflow* and *maximum economic loss* attributes. Based on these results, we retained three ANA patterns (ANA-cash outflow, ANA-maximum economic loss, and ANA-cash outflow + maximum economic loss) for further investigation.

We identified the EBA processes that might be present in the data using a latent class choice model and used this intermediate step to screen-out the unused EBA decision-processes. The detailed presentation of the procedures and results are presented in Annex D. The results suggested that the probabilities associated with EBA-cash outflow, and EBA-maximum economic loss were very small and not significant. A second RUM-EBA model with one full compensatory class and the three remaining EBA classes (i.e., EBA-income, EBA-labour and EBA-lower fertility) demonstrated a better fit of the data. We retained these four classes for the final model.

5.3. Joint evaluation of RUM, EBA, and ANA

We estimated models including two and three preference classes. For each preference class, we factored one RUM decision process, the three ANA, and the three EBA decision processes detected in previous sections. The models using three preference classes led to inconsistent classes, and therefore we have only retained models with two preference classes.

The results of this joint model, not presented here for sake of space, showed that the probability of using the "ANA-Cash outflow + Maximum economic loss" was not significant. Therefore, we ran a second joint model that included two preference classes factored by one standard RUM decision process, two ANA (ANA-cash outflow and ANA-maximum economic loss), and three EBA (EBA-income, EBA-labour, EBA-fertility) decision processes, leading to $2 \times (1+2+3) = 12$ latent classes. Hence, we estimated two vectors of preferences (2×7 parameters) and 11 θ parameters related to the class probabilities.

Table 4
Estimated parameters of the latent class model with RUM, EBA, and ANA processes.

Attributes	Coefficient[†]	Std. Err.	Sig [††]
Preference Class 1			
ASC	−0.386	0.198	**
Income	0.147	0.046	***
Labour	−0.064	0.056	
Cash outflow	−0.021	0.064	
Max. Economic Loss	−1.658	0.227	***
Higher Fertility	1.924	0.310	***
Lower Fertility	−2.847	0.579	***
Preference Class 2			
ASC	−1.332	0.459	***
Income	0.381	0.132	***
Labour	−0.324	0.135	***
Cash outflow	−0.349	0.191	***
Max. Economic Loss	−0.797	0.189	***
Higher Fertility	1.717	0.521	***
Lower Fertility	−0.367	0.995	
Class parameters			
RUM 1 [†††]	−2.859	3.209	
ANA-Cash 1	−2.879	3.186	
ANA-Maximum Economic Loss 1	−0.416	0.542	
EBA-Income 1	−1.958	0.785	**
EBA-Labour 1	−0.880	0.394	***
EBA-Fertility 1	−1.015	0.912	
RUM 2 [†††]	−4.269	2.611	.
ANA-Cash 2	−2.411	0.665	***
ANA-Maximum Economic Loss 2	−3.971	2.655	
EBA-Income 2	−3.811	1.723	**
EBA-Labour 2	−5.985	3.171	**
EBA-Fertility 2	0	0	
Model Statistics	K = 25; LL = −528.43; LR Test (compared with CL): 490.74, df = 18 (p = 0.000) AIC = 1106.85; BIC = 1221.33 D-error = 0.129		

† For better convergence of the subsequent models, the attributes have been scaled. The attributes for Income, Labour, Cash outflows have been divided by 10, and the Maximum Economic Loss has been divided by 1,000,000. The fertility attribute has been effect coded.
†† ***, **, * indicates significance at 1%, 5%, 10% level.
††† RUM corresponds to the full compensatory model.

The results of this second and final model are presented in Table 4. They suggested that the respondents had a very small probability to use a standard full compensatory decision process but rather indicated that respondents had a high probability of using one of three decision-making processes: EBA-fertility ($p = 0.35$), ANA-maximum economic loss ($p = 0.24$) or EBA-labour ($p = 0.15$). Other tested processes were also likely to be present but with a much lower probability ($p < 0.05$ for each process).

Based on the results of Table 5, we also tested a model where we dropped the combination of preference and heuristics with non-significant probabilities resulting in a model with eight classes. For sake of space, the results are presented in Annex E. They show that the results are consistent with results presented in Table 4, with only small variations in the coefficients and equivalent probabilities associated with the classes. This suggests a good stability of the classes despite our small sample size.

5.4. Discussion

The results indicate the existence of substantial heterogeneity in how farmers selected the systems they would use. This information is very useful for the development of new cropping systems.

The results suggested that farmers used one of three procedures to process the *labour* attribute. Firstly, farmers had a 15% probability to follow an EBA-labour process. It means that farmers would reject any cropping system that is too demanding in terms of labour whatever other advantages the farmer could provide. Farmers are likely to be highly labour-constrained and are not able or willing to employ outside labour to release this constraint and they will not be able or willing to take advantages of the other possible positive points of the new cropping systems. Secondly, for farmers of the Preference Class 1, the marginal utility of increasing labour requirement was not significantly different from zero implying that proposing a cropping system with lower labour requirement would not significantly increase the farmer's utility. Farmers belonging to this group are likely to have un-used labour and would not, *ceteris-paribus,* be convinced by labour-saving technologies, but would not reject labour-increasing technologies. Lastly, for farmers of the Preference Class 2, the marginal utility of increasing labour was negative and significant. For those farmers, labour-increasing technologies (such as many agro-ecological systems) would be attractive only if this can be compensated by improvement on other attributes. In terms of their willingness to accept additional labour, these farmers would require an increase of 0.85% in their income to compensate for an additional 1% labour requirement. The current cropping system costs and technical coefficients are presented in Table 6. Based on these assumptions, the necessary increase in revenue would be 4,000 (kg/ha) x 1,300 (Kip/kg) x 0.85% x 8,700^{-1} (Kip/USD) = 5.0 USD/ha. Since, the increase in labour requirements would be 0.5–0.7 days/ha, the willingness to accept in monetary units ranged from 7 to 10 USD per additional labour-day required. This is slightly above the average daily farm wages of 6–7 USD/day observed in the study area.

The results suggested that farmers used one of two procedures to process the *cash outflow* attribute. Firstly, we did not detect any EBA process, indicating that none of the sampled farmers had hard constraints. Secondly, farmers had a 5% probability to ignore this attribute. Lastly, for farmers falling into Preference Class 1, the marginal utility of increasing cash requirements was negative but not significant, while it is significantly negative when falling into Preference Class 2. When aggregating the probabilities of classes that corresponded to farmers without cash constraints (RUM2, ANA-Maximum Economic Loss 2, EBA-Income2, EBA-Labour 2, EBA-Fertility 2), the results suggested that there was a 37% probability that farmers faced cash constraints. For farmers not facing cash constraints, despite the diversity of processes, these results suggested that, either farmers carried out activities providing sufficient cash in regular basis (as suggested by the presence of weaving activities carried out by women in the sampled villages), or had a relatively good access to formal or informal credit. Finally, there is the ubiquitous possibility when dealing with stated preference, that the attribute were treated purely hypothetical by the farmers and they therefore did not pay attention to the cash outflow attribute.

The farmers had a 23% probability of ignoring the *maximum economic loss* attribute. Farmers who did not attend to the maximum economic loss are most likely risk neutral (or possibly risk-taker), since the possibility of high losses was not considered when making the choice. This also means that 77% of the sample factored the possibility of economic losses into their decision, but were ready to make trade-offs to lower that risk. This is consistent with the previous adoption studies that have identified un-insured risks as one

Table 5
Probabilities of latent classes.

Latent Class	Probability [a]	St. Error	Sig.
RUM 1 [b]	0.020	0.064	
ANA-Cash 1	0.020	0.063	
ANA-Maximum Economic Loss 1	0.232	0.078	***
EBA-Income 1	0.050	0.036	
EBA-Labour 1	0.146	0.039	***
EBA-Fertility 1	0.128	0.106	
RUM 2 [b]	0.005	0.013	
ANA-Cash 2	0.032	0.019	*
ANA-Maximum Economic Loss 2	0.007	0.018	
EBA-Income 2	0.008	0.013	
EBA-Labour 2	0.001	0.003	
EBA-Fertility 2	0.352	0.088	***

[a] Only prior probabilities are reported here since estimated prior probabilities and mean posterior probabilities provided almost similar results.
[b] RUM corresponds to the full compensatory model.

Table 6
Characteristics of an average maize cropping systems in the study area.

	Average value	Unit
Yield	4,000	Kg/ha
Price	1,300	Kip/Kg
Exchange rate	8,700	Kip/USD
Labour requirements	50–70	Man-days
Cash Requirements	2,000,000–2,500,000	Kip/ha

important explanation for low investment in agriculture and slow adoption of alternative systems (e.g., Karlan et al., 2014; Ullah et al., 2015). However, the presence of a significant population of risk-neutral farmers is important for technology promoters, since they probably represent farmers that are more willing to test new technologies without the need for a more efficient insurance markets. However, as the probabilities of these losses occurring were not part of the attribute description, further research would be needed to better characterize farmers' attitude towards risk.

For the *fertility* attribute, the results indicated a very high probability (48%) of using the EBA-lower fertility. This suggested that any cropping systems suspected to degrade soils is likely to be rejected by around half of the farmers whatever other advantages they would provide. For other farmers, the two coefficients for fertility also indicated a strong concern by farmers of the region for this attribute. This suggested that soil conservation or enhancing cropping system would raise the interest of farmers of the region, as most respondents would be ready to lose immediate income to be able to improve their soil fertility over time, or avoid reducing it. This result was expected since most farmers have been using continuous maize cropping systems without using organic or chemical fertilizers and had indicated increasing problems with the fertility of their soils. However, this also suggests that more in-depth research is required. While many farmers showed high negative willingness to pay for soil fertility losses, or outright rejection of degrading cropping systems, many have been using techniques affecting soil fertility. This suggests that farmers either (a) answered strategically or (b) some form of social bias led them to give artificially high importance to that attribute, or (c) gave rational answer as they are starting to concentrate on soil fertility issues when the cost of fertility losses are becoming high (as it is now in the survey area). In the latter case, this would suggest that time is right for changes to occur in their cropping systems. The hypotheses (a) and (b) can be made since CE is based on farmers' statements and not on real-life decisions, leaving room for biases in the answers. The surveyors conducted their research on behalf and presented themselves as belonging to an agricultural research centre. However, when presenting their activities, they did not put any particular emphasis on the systems related to the improvement of soils, which would minimize the possibility of social bias (i.e., the farmers answering what they expect that surveyors would like to hear from them). Furthermore, the reward of the adoption would come as an improvement along the different attributes presented and not some form of external subsidy obtained from a specific project or policy specifically presented to farmers. Again, this reduces considerably the possibility of strategic answers aimed at obtaining subsidies in the future (hypothesis a). The hypothesis (c), rational farmers, would be consistent with the soil conservation literature as explained, for example, in Pagiola (1993): "… *observing agricultural practices that degrade soil does not necessarily imply that farmers have adopted unsustainable practices; they may simply be drawing down their soil stocks to their optimal long-run level*". Applied to our case study, the agricultural practices observed during the transition from traditional diversified agriculture to mono-cropping maize that led to the reduction of the soil fertility stocks could be a rational behaviour: farmers were better off making use of the important initial soil fertility stocks and reduce them up to level where further degradation is becoming more costly than conservation measures. When this stage is reached, farmers are ready to invest to maintain soil fertility levels. As the impact on fertility came out as an important attribute, and to choose conclusively between the two hypotheses, we would need to conduct additional experiments where we would identify the current soil fertility levels of the interviewed farmers and study the relation between lower current soil fertility and the value attributed to the fertility attribute. Working in contrasted areas in terms of soil fertility levels would also be useful. Additionally, we would need to seek, with farmers, a more quantitative approach to define the attribute "increased/decreased soil fertility" in a quantitative way (as compared to the two dummies we have used here). As a preliminary idea, we could define the fertility loss as the expected reduction in yield (after a time horizon to be defined) if no conservation or external inputs are used during that period, but additional work on the way farmers are evaluating soil fertility would be needed.

6. Conclusion

This paper developed a methodology to pre-screen ANA classes and then jointly detect the presence of EBA and ANA behaviour in a DCE evaluating alternative cropping systems. The methodology was used to detect a mixture of different decision strategies to explain the choices stated by farmers about prospective sustainable systems. The approach uses a latent class structure that has been adapted to integrate different decision processes into different classes. In order to reduce the number of classes to be tested we used approach proposed by Vij and Krueger (2017) that proved useful in reducing the number of ANA classes to be tested. The resulting model is highly flexible and able to accommodate a large spectrum of processes. We demonstrate in the paper how the model can accommodate the three different decision strategies (compensatory, EBA or ANA) instead of assuming only one heuristics being used.

In our choice data, we found that the sample of farmers was using different decision rules when choosing between agricultural technologies. This result has important consequences for the promotion of agro-ecological technologies as we should not expect all farmers to assess the technologies in terms of trade-offs between positive and negative aspects of the adoption. For an important share of the farmers, promoting the better side of the technologies will not result in higher probability of adoption as long as their "hard" constraints are not solved. For our specific case, technologies that increase risk of failure or labour requirements will likely be rejected by a large share (25% + 15%) of the farmers whatever the other beneficial impact these technologies could have. The implications should concern both the policy makers and the technology developers. For this relatively large share of farmers, enabling environments (e.g. creation of safety nets mechanisms for the adopters, improvement of the labour market functioning) might be factors that policymakers could consider in order to increase uptake of agricultural technologies. For developers, constraints on labour should be considered e.g. reduce the labour requirements by using different input combinations. We acknowledge that our results are affected by the construction of the choice task we presented to the respondents and therefore serves only as an indication of what might be at play, which could be further tested by using e.g. randomized control trials in future research.

Author statement

Damien Jourdain: Conceptualization, Data collection, Formal analysis, Writing-; Juliette Lairez: Conceptualization, Data collection; Bruno Striffler: Conceptualization, Data collection, Writing; Thomas Lundhede: Formal analysis, writing.

Declaration of competing interest

All authors have approved the manuscript and agree with its submission to *Journal of Choice Modelling.* That manuscript has not been published and is not under consideration elsewhere and we have no conflict of interest to disclose.

Data availability

Data will be made available on request.

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Annex A. Choice Experiment Section of the Survey

Introduce the choice experiment

We would like to know what is important for you when you choose to grow a crop, or when you choose different techniques to grow a crop. We will proceed with a series of choices to be made.

Each time, you will be presented 3 cropping system (hereafter we will simply call it a crop), your current crop (maize) and 2 other crops (it could be maize grown differently, but it could be another annual crop). Each crop is presented with 5 characteristics: income, the labor needed, the cash outflow needed, the impact on soil fertility and the risk of failure. We will present 6 scenarios and each time you will have to choose only one crop from the 3 proposed to you.

Think carefully about the consequences of introducing these new crops on your farm. How it would influence the organization and performance of your farm. As only one system is possible, you need to remember that growing one crop would prevent you from growing the others proposed.

Please also note that, from our point of view, **there is no good or bad choice**. We are only interested in your point of view and your choices, since it would help to identify crops or cropping systems that would fit your needs and preferences.

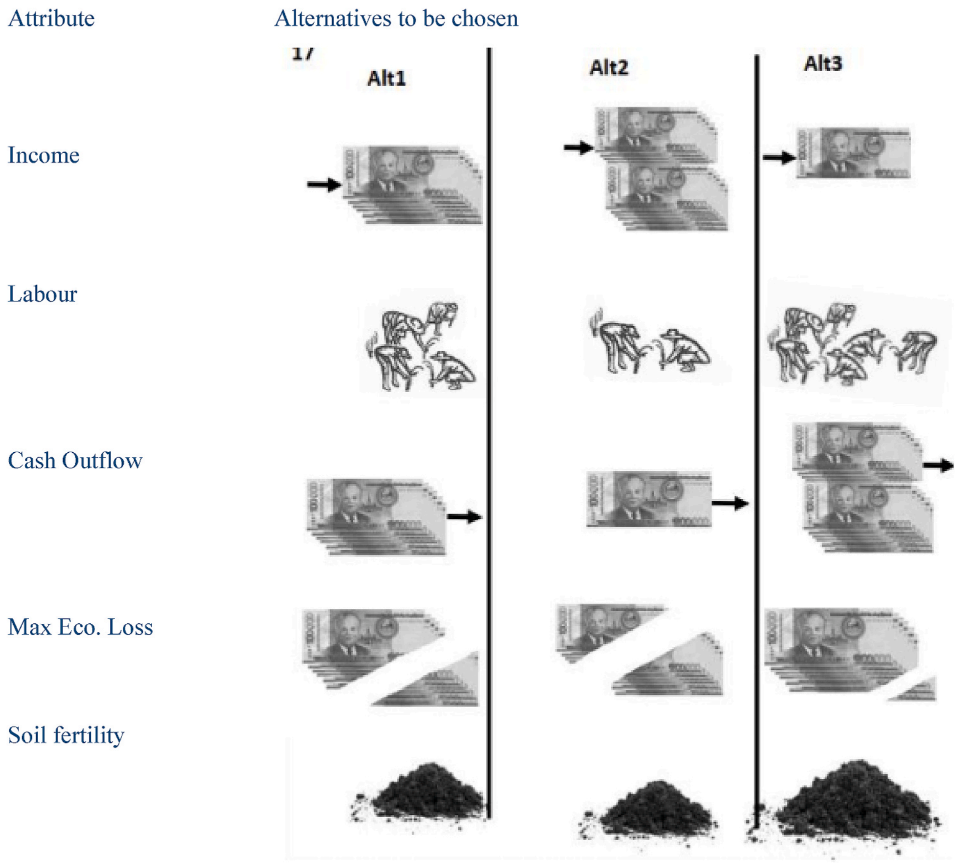
Describe and discuss the crop attributes with the farmer (together with the sheet of drawings)

1) The “Income” parameter refers to the potential benefit that you can have once your income = total yield*price. The number 100 is taken to be the same benefit that you have with maize. 80 means that for every 100 LAK that you earn from maize, you will earn 80 from this crop. 150 means that for every 100 LAK that you earn from maize, you will earn 150 from this crop.
2) The “Labour” parameter refers to the total amount of time that you (or your family members) have to spend on this crop. The number 100 is taken to be the same amount of work that you have to do with maize. 80 means that for every 100 man-days that you spend for maize, you will only spend 80 for this crop. 150 means that for every 100 man-days that you usually spend for maize, you will spend 150 for this crop.
3) The “cash outflow” parameter refers to the money that you need to spend for a crop during the cropping season (for the inputs, land preparation, seeds etc.). The number 100 is taken to be the same amount that you have to spend for maize. 80 means that for every 100 LAK that you spend for maize, you will spend only 80 for this crop. 150 means that for every 100 LAK that you spend for maize, you will spend 150 for this crop.
4) The “risk” parameter means the risk of having to endure a large income loss (during a bad year). There are three possible risk scenarios: under the current crop, we estimated that you could lose a maximum of 400,000 LAK/ha during a bad year. Cultivating

another crop could lead to the same loss risk (400,000 LAK/ha during a bad year), or higher (2 M LAK/ha), or lower (200,000 LAK/ha)

5) The "fertility" parameter means the influence of the crop on soil fertility. Soil fertility could a) remain the same, i.e. the crop does not improve or degrade the soil, b) improve over time, or c) decrease over time (the crop degrades the soil)

Explain the relationship between the pictures and the attribute[5]



Depending on the block, present the six choice sets successively (the cards are numbered with the no. of the set) and collect the choices.

Annex B. Conditional logit model with non-linear preferences for labour, cash outflow, and maximum economic losses

Table B1
Conditional logit coefficient estimates with nonlinear preferences for all attributes

Attributes	Coefficient†	St. Error	t values	Pr(>|t|)
No Change (status quo)	0.136	0.575	0.237	0.813
Other Alternatives††	−0.136	0.575	0.237	0.813
Income (less)	−1.364	0.187	−7.274	0.000
Income (base) ††	0.879	0.215	4.086	0.000
Income (more)	0.485	0.206	2.358	0.018
Labour (less)	0.750	0.153	4.894	0.000
Labour (base) ††	0.280	0.163	1.716	0.086

(continued on next page)

[5] Always remind farmers about the correspondance between the pictures and the numbers you have presented earlier; Keep the correspondance chart on the table or near the farmer so he can consult it at any time needed.

Table B1 (*continued*)

Attributes	Coefficient†	St. Error	t values	Pr(>|t|)
Labour (more)	−1.030	0.188	−5.484	0.000
Cash outflow (less)	1.166	0.371	3.141	0.002
Cash (base) ††	−1.302	0.686	−1.897	0.058
Cash outflow (more)	0.137	0.396	0.345	0.730
Max Economic Loss (lower)	0.519	0.211	2.456	0.014
Max Economic Loss (base) ††	0.144	0.209	0.690	0.490
Max Economic Loss (higher)	−0.663	0.098	−6.796	0.000
Fertility (higher)	1.675	0.142	11.796	0.000
Fertility (no change) ††	1.159	0.211	5.506	0.000
Fertility (lower)	−2.834	0.292	−9.703	0.000
Log Likelihood (LL)	−556.67			
LL (constants only)	−773.86			
AIC	1135.35			
BIC	1185.73			
D-Error	0.0172			

† The attributes status quo, benefit, labour, cash outflow, maximum economic loss, and fertility were effect coded.
†† The coefficient of the base level for each attribute were calculated as the negative of the sum of the coefficients for the other levels. Their standard deviation were calculated using the Delta method.

Annex C. Identification of Attribute Non-Attendance using the latent class choice model with unequal grid (Vij and Krueger, 2017)

We ran the Vij and Krueger model with unequal intervals and three mass points to characterize the distribution of the Alternative Specific Constant (ASC) coefficient that describes the status quo alternative, four mass points to characterize the distribution of the income, labour, cash outflow and maximum economic loss coefficients, and two mass points to characterize the distribution of the high and low fertility coefficients. We also imposed constraints on the signs of the preference coefficients (negative for the *labour*, *cash*, *max. economic loss* and *lower fertility* coefficients, positive for the *income* and *higher fertility* coefficients). The starting values for the boundaries of the grid for each coefficient are presented in Table A1.

Table C1
Starting values for the boundaries of the hi-dimensional parameters grid

	Lower Bound	Higher Bound
ASC	−3	0
Income	0	1
Labour	−2	0
Cash outflow	−2	0
Maximum Economic Loss	−2	0
Lower Fertility	0	4
Higher Fertility	−4	0

The estimated location of the mass points used to evaluate the random preference coefficients are presented in Table A2. The results indicated that latent class choice model with unequal grid was able to uncover patterns of ANA and to distinguish it from low sensitivities to the same attributes. In particular, the results suggested that ANA was used as a decision rule with respect to the two attributes *cash* and *maximum economic loss,* with 58% and 18% of the sample population likely insensitive to those attributes.

The model results also suggested that all individuals attended other attributes but with contrasted patterns. The fertility attribute was always attended and the location of the mass points suggested high preferences for these attributes. By contrast, for the income and labour attributes, a significant proportion of the population seemed to have a very small sensitivity to these attributes with 42% and 62% share for the close to zero income and labour mass points. Lastly, the joint probability mass function (Figure A1) suggests that around 12% of the sample population ignored simultaneously the risk and cash attributes.

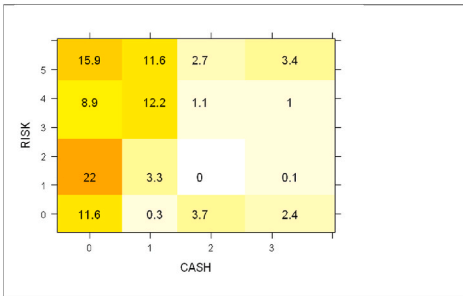
Table C2
Estimated location and marginal probabilities of each of the mass points along the random taste coefficients under the latent class choice model with unequal grid specification.
Based on these results, we retained three ANA patterns (cash outflow NA, maximum economic loss NA, and cash outflow + maximum economic loss NA) for further investigation.

	Points	Est.	St. Err.	Share (%)
ASC	1	6.08	1.02	29
	2	−1.15	0.55	36
	3	1.21	0.32	35

(*continued on next page*)

Table C2 (*continued*)

	Points	Est.	St. Err.	Share (%)
Income	1	0.11	0.07	42
	2	0.52	0.07	22
	3	1.52	0.09	20
	4	2.31	0.11	16
Labour	1	−3.75	0.13	9
	2	−2.13	0.10	7
	3	−1.12	0.08	23
	4	−0.14	0.06	61
Cash outflow	1	−3.30	0.15	7
	2	−1.82	0.10	7
	3	−1.07	0.10	27
	4	0.00	0.07	58
Max. Economic Loss	1	−5.34	0.52	34
	2	−3.88	0.68	23
	3	−1.29	0.40	25
	4	0.00	0.26	18
Lower fertility	1	−13.55	0.92	73
	2	−8.02	1.02	27
Higher fertility	1	4.87	0.46	50
	2	11.59	0.56	50
Log Likelihood (LL): −475.32				



	Joint Probability
Full Attendance	35.3%
Cash outflow NA	46.7%
Max. Economic Loss NA	6.4%
Cash outflow + Max. Economic Loss NA	11.6%

Fig. C1. Joint probability mass functions for the cash outflow and maximum economic loss parameters

Annex D. Identification of Elimination-By-Aspects

First, we estimated a RUM-EBA model with five EBA classes (each class corresponding to EBA related to one attribute). The results are presented on the left side of Table D1 and suggested that the probabilities associated with EBA-cash outflow, and EBA-maximum economic loss were very small and not significant. Therefore, we estimated a second RUM-EBA model with one full compensatory class and the three remaining EBA classes (right side of Table D1).

This second RUM-EBA model improved the likelihood to −532.4 from −581.9 for the conditional logit, but using 14 additional parameters. Despite this important increase in the number of parameters, it showed an improvement in terms of Bayesian Information Criteria.

Table D1
Estimated parameter of the latent class model considering only Elimination by Aspects

	EBA All EBA Classes considered			EBA INCOME/LABOUR/FERTILITY		
Attributes	Est.	Std. Err.	Sig.	Est.	Std. Err.	Sig.
Preference Class 1						
ASC	−0.507	0.381		−0.933	0.227	***
Income	0.077	0.084		0.161	0.051	***
Labour	−0.286	0.126	***	−0.065	0.061	
Cash outflow	−0.037	0.113		−0.035	0.081	
Max. Economic Loss	−1.786	0.391	***	−0.468	0.119	***
Lower Fertility	2.127	0.457	***	1.832	0.337	***
Higher Fertility	−3.262	0.837	***	−1.820	0.652	***
Preference Class 2						
ASC	−0.945	0.215	***	−0.397	0.342	
Income	0.158	0.050	***	0.074	0.080	

(continued on next page)

Table D1 (*continued*)

Attributes	EBA All EBA Classes considered Est.	Std. Err.	Sig.	EBA INCOME/LABOUR/FERTILITY Est.	Std. Err.	Sig.
Labour	−0.067	0.060		−0.252	0.120	***
Cash outflow	−0.026	0.082		−0.072	0.099	
Max. Economic Loss	−0.479	0.118	***	−1.688	0.339	***
Lower Fertility	1.939	0.386	***	2.076	0.460	***
Higher Fertility	−2.051	0.761	***	−3.080	0.843	***
Class Probabilities						
RUM (1)	0.0237	0.0708		0.1823	0.1341	
EBA - Income (1)	0.0776	0.0353	***	0.0645	0.0382	*
EBA – Labour (1)	0.1175	0.0505	***	0.0024	0.0075	
EBA – cash outflow (1)	0.0374	0.0504				
EBA – maximum economic loss (1)	0.0029	0.0093				
EBA – Lower fertility (1)	0.045	0.0971		0.4272	0.162	***
RUM (2)	0.2202	0.2022		0.0249	0.0811	
EBA – Income(2)	0.0697	0.0376	*	0.0736	0.0363	***
EBA – Labour (2)	0.0028	0.0087		0.1235	0.0491	***
EBA – Cash outflow (2)	0.0226	0.0504				
EBA – Maximum economic loss(2)	0.0025	0.0077				
EBA – Lower fertility (2)	0.3781	0.2354	*	0.1017	0.1063	
Model statistics	K = 25; LL = −532.53; AIC = 1,115.07; BIC = 1,229.55			K = 21; LL = −532.41; AIC = 1,106.83; BIC = 1,202.99		

Annex E. Stability of classes when eliminating classes with small posterior probability of occurrence

Table E1
Estimates of model with two preference classes and six heuristics†.

Attributes	Estimate	St_Error	t values	Pr(>|t|)
Preference Class 1				
No Change (status quo)	−1.215	0.392	−3.101	0.002
Income	0.370	0.120	3.078	0.002
Labour	−0.292	0.117	−2.501	0.012
Cash outflow	−0.317	0.172	−1.849	0.064
Max. Economic Loss	−0.762	0.183	−4.163	0.000
Higher Fertility	0.132	0.898	0.147	0.883
Lower Fertility	1.576	0.493	3.197	0.001
Preference Class 2				
No Change (status quo)	−0.416	0.194	−2.148	0.032
Income	0.147	0.046	3.174	0.002
Labour	−0.066	0.056	−1.172	0.241
Cash outflow	−0.023	0.063	−0.367	0.714
Max. Economic Loss	−1.659	0.225	−7.363	0.000
Higher Fertility	−2.794	0.573	−4.877	0.000
Lower Fertility	1.883	0.303	6.210	0.000
Class parameters				
RUM1	−2.906	2.062	−1.409	0.159
ANA-CASH1	−1.331	0.825	−1.614	0.107
EBA-FERT1	0.870	0.666	1.306	0.191
RUM2	−2.054	3.626	−0.566	0.571
ANA-MEL2	0.440	0.677	0.650	0.515
EBA-INC2	−1.069	1.020	−1.049	0.294
EBA-LAB2	−0.012	0.673	−0.018	0.986
EBA-FERT2	0	0	0	0
No. of parameters	21.0			
AIC	1082.86			
BIC	1179.03			
D-Error	0.0563			

† The combination of preference class and heuristic was based on the results of model presented in the paper where we kept the combination that had significant mean posterior probabilities.

Table E2
Prior probabilities of latent classes

Class	Prob.	St. Error	Z	
RUM1 †	0.008	0.199	0.041	0.967

(*continued on next page*)

Table E2 (*continued*)

Class	Prob.	St. Error	Z		
ANA-CASH1	0.039	0.080	0.490	0.624	
EBA-FERT1	0.355	0.073	4.860	0.000	***
RUM2 [†]	0.019	0.324	0.059	0.953	
ANA-MEL2	0.231	0.070	3.294	0.001	***
EBA-INC2	0.051	0.087	0.584	0.559	
EBA-LAB2	0.147	0.058	2.530	0.011	**
EBA-Fert2	0.149	0.107	1.385	0.166	
No. of parameters	21				
AIC	1082.86				
BIC	1179.03				
D-Error	0.0563				

[††] The probability of the full compensatory models were not significant in most models, but are kept since they are needed to evaluate the preference coefficients.

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