AGRICULTURAL MULTI-FUNCTIONAL VEHICLES AND THE ENVIRONMENT: CHOICE EXPERIMENTS AND RANDOM UTILITY MODELS FOR INVESTIGATING RENEWABLE ENERGIES

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Abstract. *In this paper the preferences of agricultural firms towards environmental investments in multi-functional vehicles are analysed through a choice-experiment and the application of multinomial discrete choice models. Furthermore, recent theoretical issues regarding this methodology have been taken into account by considering the heterogeneity of respondents as well as the heteroschedasticity of the error terms across alternatives. More precisely, the Heteroschedastic Extreme Value model is applied in order to further investigate the variability of respondents when choosing between vehicles with relevant technological differentiations, such as fuel and product performances.*

Keywords: *Choice Experiments, Random Utility Model, Heteroschedastic Extreme Value model.*

1. INTRODUCTION

In literature, preference measurements and choice experiments are considered the main methods for studying and analysing the consumer's decision-making in order to improve his/her utility in changing a service or product. In particular, the preference theory must be evaluated according to the nature and definition of preference, namely, revealed or stated preferences and, in case of stated preferences, we can distinguish among contingent valuation, conjoint analysis and choice modelling, for articulated reviews see Netzer *et al.* (2008), Berni and Rivello

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(2009). Nevertheless, by considering conjoint analysis and choice modelling, the theoretical elements of distinctions are positively overlapped or interchanged and this classification is not so clearly definable; therefore these methods are generally defined as multi-attribute valuation methods. Moreover, the related statistical models have been developed separately in the last few decades (Lenk *et al*., 1996; McFadden and Train, 2000; Greene and Hensher, 2003); however recent developments in this field have been directed mostly towards improving common features, such as the heterogeneity of respondents (Fiebig *et al*., 2010) and the complexity of the alternatives, which are called profiles in the conjoint analysis situation.

Undoubtedly, the main distinction between conjoint analysis and choice modelling is the monetary evaluation, that is, the so-called willingness to pay (Scarpa *et al*., 2007), which is the quantitative expression of the respondents regarding their willingness to accept a change in the product concerned or in a single attribute. Furthermore, when considering a Choice Experiment (CE), the respondent is asked to give his/her preference within each supplied choice-set, which is formed by a set of alternatives and selected from an experimental design; several choice-sets are usually supplied to each single respondent.

This paper focuses on the application of Choice Experiments and Random Utility Models (RUM) in the agricultural field. More precisely, preference measurements are analysed in order to improve the use of solar powered electrical multi-functional vehicles on farms. By considering the heteroschedasticity of the error terms and the heterogeneity of respondents as the two relevant issues of the applied method, this study focuses on the stated interest of farmers to invest in environmental multi-functional vehicles taking into account the specific heterogeneity of the farmers and the variability through alternatives.

Within the framework of choice modelling, we summarise our theoretical and empirical contributions as follows:

1. a set of three choice-sets is supplied in order to evaluate the use of renewable energies in agriculture through three different vehicles: RAMses, Better and ProGator; each respondent is asked to give his/her preference on a set of three alternatives according to a multinomial choice;
2. the evaluation of these three vehicles takes into account: i) the main characteristics of these machines, such as fuel and fuel distance; ii) the characteristics of farms and related owners; to do this, an ad-hoc questionnaire is supplied to respondents together with choice-sets;
3. in order to deal with the two points mentioned above, discrete choice models with a binary response variable are applied; in particular, the simple Conditional

MNL logit model is used as a preliminary model; the Mixed Multinomial Logit model (Mixed MNL) and the Heteroschedastic Extreme Value model (HEV) are subsequently applied to evaluate the respondents' heterogeneity and the heteroschedasticity of the error term by considering the relaxation of the Independence of the Irrelevant Alternatives (IIA) assumption.

The paper is organized as follows: Section 2 contains a brief description of the theory relating to the discrete choice models; Section 3 includes the case study, the data and variables description; the outcome of the model results and the discussion are reported in Section 4; final remarks follow in Section 5.

2. OUTLINED THEORY

As an initial step, the class of Random Utility Models (RUMs) is defined. In general, every alternative is indicated by *j,* so that the choice-set is formed by *J* alternatives: $\{1, ..., J\}$, while *i* denotes the respondent ($i = 1, ..., I$). In the class of RUMs, the individual *i* who chooses the alternative *j* has a random utility U_{ij} that may be generally expressed as in formula (1). Furthermore, it is assumed that the respondent *i* maximises his/her utility by choosing the alternative j, belonging to the choice-set C, so that U_{ij} is the highest of all the utilities U_{ik} $k = 1, ..., J.$ Thus, the following expression is characterised by a stochastic utility index $U_{ij},$ which may be expressed, for each unit i, as a linear function of the attributes for the alternative *j,* as:

$$\begin{aligned} U_{ij} &= V_{ij} + \varepsilon_{ij} \\ V_{ij} &= x_{ij}^{'}\beta \end{aligned} \tag{1}$$

where V_{ij} is the deterministic part of the utility and is defined here in relation to a vector x_{ij}, containing the characteristics of respondent *i* and alternative *j,* β is the vector of unknown coefficients and ε_{ij} $j = 1,...,J$ is the random component. The random component is generally supposed to be independent and also Gumbel or type I extreme value distributed. The following formula (2) defines the cumulative function of the Gumbel distribution:

$$F\left(\varepsilon_{ij}\right) = \exp\left(-\exp\left(\varepsilon_{ij}\right)\right) \tag{2}$$

It must be noted that each alternative will be characterised by a vector of characteristics (attributes); following this, the fuel, noise level, price, monthly cost of vehicle maintenance and the farm's characteristics are analysed.

2.1 MULTINOMIAL LOGIT MODEL AND HEV MODEL

The Multinomial Logit Model (MNL) is the simpler model belonging to the RUM class; in fact, for this statistical model, the IIA property is hypothesised and this means that the choice probability in one choice-set is independent from the presence of other attribute values or any other alternative; on the other hand, we may say that IIA derives from the hypothesis of independence and homoschedasticity of the error terms.

The relaxation of this assumption (Train, 1998), performed through the following applied HEV model, makes it possible to highlight the real impact of each attribute on the respondent's preference. The term "conditional" shows that the unit *i* chooses the alternative *j,* which belongs to a set of alternatives called choice-set C and the applied model is called Conditional MNL logit. Consequently, the probability of the unit *i* to choose the alternative *j* is defined as:

$$P_{ij} = \frac{\exp\left(x'_{ij}\beta\right)}{\sum_{k=1;k\in C_i}^{J}\exp\left(x'_{ik}\beta\right)} \tag{3}$$

where x_{ij} denotes the vector of attributes for the alternative *j* presented to the unit i and it corresponds to the deterministic term of formula (1).

It must be noted that the subscript i for the choice-set C in formula (3) denotes each specific choice-set supplied to the respondent *i.* In this case, the error term is supposedly distributed as in formula (2); therefore, in this case the evaluation of the error alternatives is not included, i.e. this model assumes equal variances on random components of utility for all the alternatives.

By considering formula (3), it is easy to observe the practical limit of the IIA property. In fact, if we compare two alternatives, *j* and *k,* we can see how the ratio is only expressed on the attribute values included in these two alternatives, without evaluating any other alternatives:

$$\frac{P_{ij}}{P_{ik}} = \frac{\exp\left(x'_{ij}\beta\right)}{\exp\left(x'_{ik}\beta\right)} = \exp\left(x'_{ij} - x'_{ik}\beta\right) \tag{4}$$

The Heteroschedastic Extreme Value (HEV) model (Bhat, 1995) also belongs to the RUM class, formula (1). The main feature of this model concerns the modified assumptions on the random component, which is supposedly distributed as a type I extreme value distribution, formula (6), independently but not identically distributed. It must be noted that this different hypothesis on the random component makes it possible to treat the relaxation on the IIA property differently; this relaxation is fundamental and strengthens improvement with respect to the basic MNL logit model.

Furthermore, in the HEV model, different scale parameters between alternatives are estimated. The main evident advantage is that the scale parameters may be defined as the weights in order to measure the uncertainty relating to the alternatives and the attributes involved. Moreover, the presence of large variances for the error terms influences the effects of changing the systematic utility for the generical alternative *j.* Therefore, the probability that a respondent i chooses the alternative *j* from the choice-set C_i is:

$$P_{ij} = \int_{\varepsilon} \prod_{k \in C_{i;k \neq j}} \Lambda \left\{ \frac{x'_{ij}\beta - x'_{ik}\beta + \varepsilon_{ij}}{\theta_k} \right\} \frac{1}{\theta_j} \lambda \left(\frac{\varepsilon_{ij}}{\theta_j} \right) d\varepsilon_{ij} \tag{5}$$

with the error term distributed as follows:

$$f\left(\varepsilon_{ij};\theta_j\right) = \lambda\left(\frac{\varepsilon_{ij}}{\theta_j}\right) = \exp\left(-\frac{\varepsilon_{ij}}{\theta_j}\right) \exp\left\{-\left[\exp\left(-\frac{\varepsilon_{ij}}{\theta_j}\right)\right]\right\}. \tag{6}$$

In formula (5), θ_j is the scale parameter for the *j* alternative and $\lambda(\cdot)$ is the probability density function of the Gumbel distribution, as in formula (6), while Λ in formula (5) is the corresponding cumulative distribution function evaluated by considering two distinct choices for the *i*-th respondent; in fact, the term $x'_{(\cdot)}\beta$ denotes the deterministic part of utility of formula (1) related to alternative *j* and alternative *k,* respectively. Note that the integral function is defined on the domain
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$[-\infty, +\infty]$ of the random component ε related to the unit i and the alternative *j.* In this case, preferences of respondent *i* are evaluated by considering a scaling term θ_j for the alternative *j* in the choice-set C_i, i.e. the heteroschedasticity of the error term. In the following case-study, three alternatives are included in each choice-set and therefore two scale-parameters could be estimated.

With respect to the MNL logit model, the HEV model and the Mixed MNL logit model, defined in McFadden and Train (2000), could be considered as competitive models for identifying and measuring the presence of an over-dispersion when modelling the respondent preferences. Following are the results of the MNL logit and HEV models; the application of Mixed MNL logit model has not provided significant results by considering the random parameters associated with the specific attributes of alternatives (mixing term). Furthermore, when the MNL logit model is reported, a test for homoschedasticity of the utility function has been carried out through the likelihood ratio by performing the difference between the estimated log-likelihood values relating to the MNL logit and the HEV models.

3. THE CASE STUDY

The case-study involved 137 plant nursery farms, located in the province of Pistoia (Italy). Farmers were asked to give their preferences regarding three choice-sets (N=411 stated preferences), each formed by three alternatives, relating to three vehicles (A: RAMses, electrical; B: Better, bio-fuel; C: ProGator 2030A, diesel).

It must be noted that three markets (M1, M2, M3) were analysed in order to assess the probability of choosing from among different vehicles, RAMses and other two tractors supplied by the real market, with particular focus on the environmental performances of the electrical one. Each market corresponds to a single choice-set formed by three alternatives relating to the three vehicles. The first market (M1), whose corresponding scenarios are shown in Tables 2 and 4, is defined by considering realistic baseline technical and economical values supplied by the tractor market with the exception of the multi-functional RAMses, a prototype not yet available on the market. Therefore, its economical values are defined according to production costs. It is pointed out that the response variable is defined as the choice of one of the three alternatives.

A questionnaire is supplied together with choice- sets. Some attributes, each with three levels, involved in the experiment are: price (range 19, 000 – 40, 000 euro; levels-M1: 35,000-40,000-19,700 euro), monthly cost (range 100 – 360 euro; levels-M1: 357-280-108 euro), power (levels-M1: 12.0-17.7-66.0 KW), emissions (0-3.6-7.2 Kg/h) and noise level (low-medium- high). With respect to the farm's characteristics and the questionnaire, we considered: age of farmer/respondent (three intervals: < 40; $41 – 55$; ≥ 55 years); farm size (three intervals: < 1; $1 – 4$; > 4 hectare); amount of investments (three intervals: $< 100, 000$; $100, 000 – 500, 000$; $> 500, 000$ euro); Q21- family-run farm (yes/no); Q24- the presence on the farm of the electrical vehicles for transporting people (yes/no); Q61- the stated interest in purchasing a multi-functional vehicle energised by a photovoltaic battery (PV) (RAMses prototype) (yes/no).

Two constants are created in order to analyse the choice preferences between: i) RAMses and bio-fuel (const-B); ii) RAMSses and diesel (const-C). It must be noted that the evaluation of constants includes the natural differences between vehicles; in fact, when comparing RAMses and bio-fuel, as well as RAMses and diesel, the differences in fuel and fuel distance are implicit. In addition, the related dummies are computed for each explicative variable; for example, by considering the farm size and the amount of investments, three classes and six dummies are created. More specifically, when considering each of the three classes of the variable investment, two dummies are created (namely, investment-B and investment-C for the class < 100,000euro in Tab. 2), where the suffices B and C have the same meaning as with the constants. The statistical analysis was started by considering all the previously mentioned variables and attributes and their potential associations; however, three main topics are identified by a selection of the best results obtained through the applied statistical models:

1. topic no.1: noise, monthly fuel cost and photovoltaic battery cost (M-Cost), presence on the farm of electrical vehicles (Q24), stated interest in purchasing electrical vehicles (Q61), family-run farm (Q21);
2. topic no.2: investments (INV), stated interest in purchasing electrical vehicles (Q61), monthly fuel cost and photovoltaic battery cost (M-Cost), product price;
3. topic no.3: age of farmer (age), monthly fuel cost and photovoltaic battery cost (M-Cost), farm size.

For each topic, the RUM models illustrated in Sections 1 and 2 are applied. Following, the most relevant results are reported by considering the estimates of coefficients, with standard errors and p-values. The correlation matrix of parameter estimates is always evaluated; values are reported when relevant for the discussion. Furthermore, scenarios and elasticities are illustrated for the real market described herein. It must be noted that the choice probabilities and the elasticities are calculated on the price or the cost difference for each pair of vehicles (RAMses versus bio-diesel or RAMses versus diesel), according to the market condition.

The fitness of the multinomial discrete choice models is evaluated through: the maximum gradient element, the number of iterations to reach convergency, the Likelihood Ratio (LR), Akaike's index (AIC) and McFadden's LR index (Mc-Fadden LRI), bounded in [0, 1], and defined as complementary to one of the LR.

4. RESULTS

All 137 farmers gave their preferences according to the three supplied choice- sets, i.e. each farmer expressed three choices; therefore, we have N=411 stated preferences for each estimated model.

It is relevant to say that the three markets are considered jointly in all the estimated models. The discrete response profile, i.e. the frequency distribution of the three alternatives, equals:

$$\text{choice} - A : 61(14.8\%)$$
$$\text{choice} - B : 275(66.9\%)$$
$$\text{choice} - C : 75(18.2\%)$$

For the sake of brevity, results relating to the topic no.1 are not reported: when considering the noise attribute, respondents always prefer the vehicle A to both B and C with highly significant p-values. Utility is significantly influenced by the presence of electrical vehicles on the farm. The correlation matrix of estimates shows interesting results: noise attribute and Q24 estimates have negative correlations with estimates of constants; conversely, the monthly cost shows high and positive correlations with constants (0.75 and 0.86 between monthly cost and const-B, const-C respectively), this means that the stated preferences for RAMses decrease rapidly if the monthly cost increases.

The first model illustrated is the estimated HEV model regarding topic no.2, including the price, the class of investments below 100, 000 euro and the item Q61 related to the potential interest to buy electrical vehicles. In Tab. 1, respondents prefer the vehicle B to A (const-B positive), while vehicle A is preferred to C. The estimated coefficient for the initial price shows a decreasing utility for the electrical vehicle when the price is higher. The utility for the respondent who prefers vehicle B (bio-fuel) is significantly influenced by the interest in purchasing electrical vehicles on the farm (Q61-B), with a highly significant p-value. The same tendency is obtained when considering the utility for the respondent who prefers RAMses to diesel together with the Q61 variable.

Table 1: HEV model for topic no.2

variable	coefficient	s.e.	p-value
const-B	8.1992	1.6037	0.0001
const-C	-2.3228	0.9236	0.0119
INV-B	0.6097	0.3896	0.1176
INV-C	0.6913	0.4592	0.1322
Q61-B	1.4631	0.3396	0.0001
Q61-C	1.0471	0.4011	0.0090
price	-0.0005	9.1e-4	0.0001
θ_3	1.0000	0.6058	0.0988

By considering our case study and formula (5) relating to the HEV model, we should have one or two scale-parameters for each estimated model, corresponding to the heteroschedasticity created by the respondent's choice when he/she evaluates the alternatives. In Tables 1 and 3 we report the results for the HEV models with only one scale-parameter, θ_3, because these are the best fitted HEV models. Moreover, this is an interesting result because it denotes the relevant variability originating between RAMses and diesel vehicles rather than RAMses and Bio-diesel when the respondent expresses his/her choice. In fact, in Tab. 1 the scale parameter θ_3, is significant and shows the heteroschedasticity with respect to the diesel vehicle. The correlation matrix of estimates, which is very relevant in highlighting the real tendency of respondents, shows further interesting results when considering the correlation between the scale parameter and constants (–0.15 and 0.92 const-B and const-C, respectively); in fact, the high correlation value between θ_3, and const-C highlights the source of variability generated when the respondent compares RAMses and diesel tractors. Correlations between the product price and const-B and const-C are –0.99 and 0.43, respectively; this means that RAMses and bio-fuel are closer if the price of bio-fuel increases (–0.99) and that the preference between RAMses and diesel is positively influenced by increasing prices (0.43).

Tab. 2 illustrates the scenarios and elasticities. It must be noted that the probability values for choosing a scenario are calculated versus RAMses, which is the vehicle of interest. Furthermore, elasticities are calculated with two price differences: 5, 000 and 15, 000 euro, which are calculated on the basis of price levels included in the market situation illustrated here; the other two market scenarios are not reported for the sake of brevity.

The results, reported in Tab. 2, with class of investments below 100, 000 euro as evaluated in the model in Tab. 1, show a general attitude to buy the electrical tractor when the alternative is the diesel vehicle, otherwise the probability is very low, independently from the Q61 values. It is relevant to note the very low probabilities towards RAMses when the preference is expressed with respect to bio-diesel (the maximum value is achieved with price difference P_{ij} = 15,000 and Q61 = yes); conversely, very high probabilities are obtained when the alternative vehicle is the diesel one. In fact, in this last case, the maximum value of probability equals 0.99 when P_{ij} = 15, 000 and Q61 = yes.

Table 2: Scenarios and elasticities for the HEV model of topic no.2
(Elasticities between brackets- P_{ij} are the differences between price levels of the supplied choice-set related to the real market (M1))

scenario	P_{ij}: 5,000 euro	P_{ij}: *15*,000 euro
const-B; Q61=no	0.000354	0.035674
	(-2.32418)	(-6.72617)
const-C; Q61=no	0.948309	0.999479
	(-0.12018)	(-0.00363)
const-B; Q61=yes	0.001526	0.137774
	(-2.32145)	(-6.01402)
const-C; Q61=yes	0.981229	0.999817
	(-0.04364)	(-0.00128)

These results confirm the respondent's behaviour showing the tendency to maximize both the environmental and the technological performances of RAMses.

By considering elasticities, the results (Tab. 2) confirm this tendency. In fact, the elasticities values vary within a wide range [-2.0, -6.0] for the bio-fuel; while in the case of diesel, the elasticity values are close to zero (range [-0.1, 0.0]), showing a price inelastic utility. It is pointed out how in this scenario the utilities are not influenced by the Q61 variable; probably because the vehicle's price and environmental characteristics have more of an influence on the respondent's choice.

The second and last model reported here is related to topic no.3. A HEV model is applied, including the monthly cost, the respondent's age and the effect of the farm size. Tables 3 and 4 illustrate the estimates and scenarios. In Tab. 3, where the farmers are over 40 and the farm size coefficients are estimated, respondents prefer the vehicle A to C; while, bio-fuel is preferred to RAMses. Both cases show highly significant p-values. The estimated cofficient for the monthly cost shows the same tendency observed in the HEV model in Tab. 1. It must be noted that coefficients of dummies for age are always negative, i.e. positively directed towards RAMses; this indicates a significant influence of age on the utility for the respondent who prefers RAMses with respect to vehicle C. Coefficients related to the farm size are positive in both cases, and this means that the utility of the bio-fuel vehicle is influenced by farm size, with a much higher preference among farmers with medium-size farms. The correlation of estimates between θ_3 and const-B is negative (-0.09) while the correlation with const-C is higher and positive (0.74); these results are further confirmation of the higher variability when the respondent has to express a choice between the RAMses and diesel vehicles.

Table 3: HEV model for topic no.3

variable	coefficient	s.e.	p-value
const-B	3.3995	0.4945	0.0001
const-C	-3.0589	1.1400	0.0073
age2-B	-0.8896	0.3785	0.0188
age2-C	-0.3228	0.4758	0.4974
age3-B	-0.9200	0.4354	0.0346
age3-C	-1.3513	0.6008	0.0245
farm size-B	0.5665	0.3404	0.0960
farm size-C	0.3331	0.3895	0.3924
M-Cost	-0.0311	0.0061	0.0001
θ_3	1.2928	0.8834	0.1434

In Tab. 4, where scenarios and elasticities are illustrated, the probability of choosing the electrical tractor is very high; how- ever, when considering the preference of RAMses with bio-fuel, this probability is lower, particularly when the monthly cost difference equals 70 euros. The probability of choosing the electrical vehicle increases to the maximum value in comparison with the diesel tractor (const-C), independently from the monthly-cost. Furthermore, elasticities are close to zero except in the case of const-B and a cost difference of 70 euros (-1.08). This confirms that an elastic response takes place when considering bio-fuel, which seems to play the role of quasi-substitute product.

Table 4: Scenarios and elasticities for the HEV model of topic no.3

(Elasticities between brackets- Pij are the differences between monthly costs of the supplied choice-set related to the real market (M1))

scenario	P_{ij}: 250 euro	P_{ij}: 70 euro
const-B; age > 40; size=medium	0.995904	0.496400
	(-0.03133)	(-1.07871)
const-C; age > 40; size=medium	0.999994	0.999996
	(-0.00005)	(-0.00308)

5. FINAL REMARKS

In this paper choice experiments and multinomial choice models are applied in order to evaluate the preference of farmers towards a renewable-energy powered tractor; heteroschedasticity is investigated and highlighted through the application of the HEV model; satisfactory results are obtained by considering both the methodological and economic points of view.

The electrical tractor utility is positively influenced by: the attitude towards the electrical vehicle of the respondents (Q61 and Q24), the machine noise characteristics, the farm size, the highest monthly cost differences, and the "over 40" aged respondents. Nevertheless, the electrical tractor utility is negatively influenced by the product price and by the lowest monthly cost difference. The elasticities are generally negative and in some cases close to zero. The negative elasticity values confirm that there is a price elastic response in the choice of the electrical vehicle. Moreover, the elasticities close to zero are related to the diesel tractor versus RAMses, showing an inelastic behaviour in the absence of a substitute product characterised by an "environmental" attribute. Furthermore, we can consider a bio-fuel tractor as an imperfect substitute for the electrical one; while the conventional diesel tractor does not possess the characteristic of a substitute for the electrical one, consequently, the demand tends to be perfectly inelastic.

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