Choice Modelling and Forecasting Demand for Alternative-Fuel Tractors

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Abstract. This paper presents a study focused on potential demand for agricultural multi-functional electric tractor. In this context, the willingness-to-pay is investigated in order to establish the potential diffusion of an electrical solar tractor, by considering different levels of key attributes related to environmental, technical and economical characteristics of different version of alternative fuel tractors. The study is carried out through a choice-experiment and the application of multinomial discrete choice models, by considering heteroscedasticity of the respondent and heterogeneity across alternatives.

Keywords: Electric agricultural multi-functional vehicle, Environmental attributes, Random Utility Models, heteroscedastic extreme value model, Willingness-to-Pay.

1 Introduction

The increased concerns on climate change due to greenhouses gas (GHG) emissions in addition to air pollution effect on human health have given deep impulse to researches on electric vehicles. The researches are focused on exploring technology needs as well as market requirements for enhancing the electric vehicles acceptance and success in public opinion, [2]. The scientific efforts are frequently adressed to different aspects of developing electrical vehicle usage in urban contest, while have seldom analysed the application of the electric engine for agricultural purposes. Agriculture is acknowledged as a significant source of global greenhouse gas emissions, also if not all agriculture systems have the same implications in terms of contributions to climate change [22]. Industrial or conventional agricultural practices make use of high levels of agro-chemicals and high degrees of mechanization. These practices are made possible through increasing consumption of fossil fuels to power agricultural machinery and to support increased level of irrigation and chemical inputs. Reducing fossil fuel use in agriculture may be an objective for bolstering sustainability of industrial or conventional agriculture. A prototype of solar powered multi-functional agricultural vehicle (RAMseS: Renewable Energy Agricultural Multipurpose for Farmers) was developed in the research project financed by European Commission

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under the 6th Framework Program, to offer opportunities for lessening the GHG and pollutant emission in intensive agricultural system ([19]; [20]). This paper focuses on the application of Choice Experiments and Random Utility Models (RUM) to explore which factor would facilitate the farmers' acceptance of the solar tractor and which would represent barrier to its diffusion. The farmers acceptance was not exclusively determined by costs but by a complex judgement that can be hardly evaluate before the electrical tractor have been produced and supplied by the existing market. To this end, the study is carried out by applying specific RUMs, in particular the Heteroscedastic Extreme Value (HEV) model, to explore which attributes would facilitate the farmers' acceptance of the solar tractor and which would represent barrier to its success, taking into account variability across alternatives. More precisely, preference measurements are analyzed in order to investigate the consumer preferences in term of different key attributes of the solar tractor to establish which attributes are more suitable for improving the use of solar powered electrical multi-functional tractor and which are obstacles to that. Farmers were asked to focus on different level of a set of key elements: saving achievable on fuel cost, added price premium to purchase the tractor, operational costs, battery replacement costs and environmental performances. The study was carried out in the Italian nursery plant sector, an intensive industrialised production system, located in Pistoia, a Province in the North of Tuscany. The 137 farmers were asked to give their preferences to three choice-sets, each formed by three alternatives, related to three different tractor' version (A: RAMses, electrical; B: Better, bio-fuel; C: ProGator 2030A, diesel) with different environmental, technical and economic attributes level. It must be noted that the response variable is defined as the choice of one alternative on three ones. A background questionnaire was supplied together with choice-sets to analyze farmer characteristics and to describe his/her farm typology. The paper is organized as follows: Section 2 includes a brief literature review on choice modelling and a short review on alternative-fuel demand models, Section 3 describes a general introduction to the utility framework, while Section 4 contains a brief description of the theory relating to the RUMs applied in this case study, by focusing on HEV model; Section 5 includes survey and data description useful to describe this research; the outcome of the model results and the discussion are reported in Section 6; the final remarks follow.

2 Literature Review

In this section a review on choice modelling is outlined; undoubtedly, many developments and improvements in consumer/user's preferences were achieved in the last two decades. In this brief review, we focus on recent advances, for further references on choice modelling and choice experiments see also [5]; furthermore, in subsection 2.2 a brief review on stated preferences and alternative-fuel vehicle demand models is reported.

2.1 Choice Modelling Advances

By considering the experimental design and the statistical modelling, a further and clear distinction must be made when we refer to preference measurements or, more in general, to the preference theory. Hence, we deal with Stated Preferences (SP), where we define as SP the preference of a respondent related to a hypothetical scenario represented by an alternative in a choice-set. However, in the literature, some recent developments are also reported in the Revealed Preference (RP) case, which is defined as the preference of the respondent about a real situation, such as in [25].

In the Stated Preferences context a choice-set is formed by a set of alternatives, opportunely selected from an experimental design, named choice experiment; the respondent is asked to give his/her preference within each choice-set. By considering the experimental design with its optimality criteria and the related statistical models, the class of RUM is largely applied and developed in literature, see among the others: [8], [15], [16],[17], [21], [27], [31],[33].

When considering the consumer's choice modelling, experimental designs and statistical models are closely connected [29], [34] and the properties of one design affect the corresponding model. When these properties do not exist in the design, this must be taken into account in the model. This is the case of an improvement in the design optimality specifically defined for a Mixed Multinomial Logit (MMNL), [23]; on the other hand, when considering the respondents' heterogeneity, a specific design matrix for each respondent is planned [24], by including the heterogeneity evaluation directly in the design step instead of the model step. Within the choice experiment step, optimality criteria, above all D-optimality, ad-hoc algorithms and specified information matrices for the experimental design involved were entirely defined in 1990's [35]. Further developments are related to the construction of optimal or near optimal designs with two-level attributes for binary choices in the presence of the first order interactions, [28], or when optimal designs are defined with mixed-level attributes, [10]. More recently in [7] several algorithms are compared (in draws within the Pseudo Monte-Carlo simulation method) to select efficient Bayesian designs.

Note that a common feature of recent years is to create a link among designs and models together with the need of a guiding thread between manufacturers and consumers. The paper [23] reflects the strict connection between experimental designs and statistical models, because they suggest an experimental design with ad-hoc properties for a Mixed Multinomial Logit. This model, belonging to the class of RUMs, is certainly the most widely applied and developed model in recent years for the choice experiment situation. Its success is easily explained when considering the theoretical results of [15], [21], [31]. The last developments of this model include its relationship with the latent class model, in order to create a finite number of respondent groups [8], [13], [17], [26]. Nevertheless, the HEV model may be viewed as a competitive model with respect to the Mixed Multinomial Logit to measure over-dispersion and to identify the cause and the structure of such variability.

2.2 A Short Review on Alternative-Fuel Vehicle Demand Models

Most of the early researches on alternative-fuel vehicles demand are exclusively addressed to electric vehicle. Stated preference model (SP) are widely applied to forecast demand for vehicle which are not supplied by the existing market. In [2], authors implement SP models to analyse the potential demand for hypothetical alternative-fuel vehicles, including diesel vehicle in the choices. In [18], authors underline that SP models are useful to investigate potential demand for hypothetical vehicle even though the respondent's choice may be different when considering the hypothetical market and the real market; a comparison between SP and Revealed Preferences (RP) models is conducted in [32], concluding that the two models are not providing excellent prediction although SP seems to be more reliable than RP in some circumstances.

Many researches try to integrate the SP and RP to improve forecast quality. In [30], the author analysed the market share for different version of non-gasoline-powered auto vehicles, concluding that, by the year 2000, 2.3% of passenger will be transported by electric vehicles. Other studies on alternative-fuel vehicles demand consider other alternative-fuel vehicles in addition to the electric vehicles; see among the others: [1], [9], [11]. The literature on forecasting analyses includes models for elasticity calculation, [11] or willingness to pay (WTP) model, [12].

By considering the existent literature and the preferences towards electrical vehicles, the market share is very low $(3-4\%)$; these results are coherent with results obtained by the case-study illustrated in Section 5.

3 A General Framework for Utility Modeling

In order to define the discrete choice models applied in this paper, we briefly introduce the fundamental elements of the utility theory [14].

As first step, the class of Random Utility Models (RUM) is defined. In general, every alternative is indicated by j $(j = 1, ..., J)$, while i denotes the consumer/user $(i = 1, ..., I)$. Each alternative will be characterized by a vector of characteristics; in what follows, price and amount of investments, farmers' characteristic and environmental practices. Thus, the following expression is characterized by a stochastic utility index U_{ij}, which may be expressed, for each unit i, as:

$$U_{ij} = V_{ij} + \epsilon_{ij} \tag{1}$$

where V_{ij} is the deterministic part of utility, while ϵ_{ij} is the random component. The random component is in general supposed independent and Gumbel or type I extreme value distributed. In the following formulas, (2) and (3), the probability density function and the cumulative distribution function (CDF) of the Gumbel distribution are defined:

$$\lambda(\frac{\epsilon_{ij}}{\theta_j}) = exp^{-\frac{\epsilon_{ij}}{\theta_j}} exp^{-exp^{-\frac{\epsilon_{ij}}{\theta_j}}} \tag{2}$$

$$\Lambda_{ij}(\frac{\epsilon_{ij}}{\theta_j}) = exp(-exp(-\epsilon_{ij}/\theta_j)) \tag{3}$$

where θ_j is the scale parameter related to the j-th alternative.

In the RUM, the individual is assumed to choose the alternative j that gives the highest level of utility, where the alternative j belongs to the choice-set C. Let the individual's indirect utility function for the alternative j be represented by:

$$U_j(q_j, y - p_j, \epsilon_j) = V_j(q_j, y - p_j) + \epsilon_j \tag{4}$$

From the researcher's perspective, the indirect utility function has two components. The first, $V_j(q_j, y-p_j)$ represents the observable portion of the individual's indirect utility function, with vector of quality characteristics q_j, income y, and price of the single product p_j. The second component of indirect utility is ϵ_j, the unobservable part of the individual's indirect utility function.

For a given choice occasion, the individual will choose the alternative j if:

$$V_j(q_j, y - p_j) + \epsilon_j \geq V_k(q_k, y - p_k) + \epsilon_k; j \in C, \forall k \in C. \tag{5}$$

Note that, just because a part of the indirect utility function is not observable, indirect utility must be expressed by:

$$v(q, y - p) = E[\max\{V_k(q_k, y - p_k) + \epsilon_k; \forall k \in C\}] \tag{6}$$

where the expectation of the right-hand side of (6) is the researcher's expectation across the random unobservable portion of the individual's utility function. Therefore, the probability of an individual i choosing the product according to the j alternative is modelled as:

$$P_i(j) = P(j|k \in C, w_i) \tag{7}$$

where w_i represents a vector of individual specific characteristic. For the purposes of the subsequent analysis we can consider the Multinomial Logit model, which can be seen as the basic model for the conditional logit described in the next section; this probability can be written as:

$$P(y_i = j) = P_i(j) = P(j|k \in C, w_i) = \frac{exp^{v_j}}{\sum_{k \in C} exp^{v_k}} \tag{8}$$

4 The Discrete Choice Models

In order to define the discrete choice models applied and discussed in this paper, we briefly introduce the fundamental elements of the related theory; for further details see the previous cited references (Section 2.1). The class of RUM, which aims to achieve the utility maximization for the consumer, enlarges the characteristics of the Logit and Multinomial models where the IIA property is hypothesized. The relaxation of this assumption [31] is a relevant improvement because the IIA means that the choosing probability in one choice-set is independent of 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 homoscedasticity of the error terms. In addition, this can also be interpreted by considering the cross-elasticity term. In fact, IIA implies an equal proportional substitution between alternatives, [31].

Furthermore, the Logit and Multinomial models do not allow to evaluate a different behavior of the consumer; i.e. each respondent, with different baseline characteristics, is treated in a similar way (the same estimate values of attributes) according only to his/her judgement.

In order to deal with the above issues, the statistical analysis is carried out through three discrete choice models belonging to this class, and, in particular, through the Multinomial Logit Model (MNL), the multinomial mixed logit and the HEV model [6].

The Multinomial Logit Model (MNL) may be also view as conditional logit model; the term "conditional" highlights that the unit i chooses the alternative j, which belongs to a set of alternatives called choice-set C_i and then the model applied is called Conditional Logit (CL). Thus, the probability of the unit i to choose the alternative j is defined as:

$$P(y_i = j) = P_{ij} = \frac{exp(x_{ij}^{'}\beta)}{\sum_{k \in C_i} exp(x_{ik}^{'}\beta)} \tag{9}$$

where x_{ij} denotes the value of the attribute for the alternative j and the unit i. Note that, the difference is expressed through the J values of the random variable y, which indicates the choice made from the unit i. The CL model is the basic discrete choice model applied in this paper and we remark that this model assumes the IIA property; in addition, in this case, the error term is distributed according to formula (3) without the evaluation of the scale parameter θ_j, i.e. the error terms are supposed identically distributed.

When a Mixed MNL model is considered, the general expression for a RUM model becomes:

$$U_{ij} = V_{ij} + \psi_{ij} + \epsilon_{ij} \tag{10}$$

The main feature of the Mixed MNL model, or of the Mixed logit model when the choice is binary, is the possibility to assume a general continuous distribution for the ψ_{ij} called also mixing term. In fact, a density for ψ_{ij} is defined as in the following:

$$g(\psi \mid \Phi) \tag{11}$$

where the space parameter Φ contains the fixed parameters of the distribution, such as Normal, Uniform, Log-Normal. If ψ is not evaluated, then the mixed logit reduces to the simple conditional logit; in general, the unconditional probability is equal to:

$$P(y_i = j) = P_i(j) = \int_{\psi} L_i(j \mid \psi_{ij}) g(\psi_{ij} \mid \phi) d\psi_{ij} \tag{12}$$

$$L_i(j \mid \psi_{ij}) = \frac{exp(x_{ij}^{'}\beta + \psi_{ij})}{\sum_{k \in C_i} exp(x_{ik}^{'}\beta + \psi_{ik})}$$

Note that the unconditional choice probability $P_i(j)$ is the integral of the conditional probability of the logit model integrated over the distribution of $\psi_{ij}, \forall i, j$

and weighted according to the fixed parameters of the mixing term. Therefore, the mixed logit model allows to treat the heterogeneity of respondents through the random parameters associated to a specific attribute of an alternative. Nevertheless, the error term across alternative in not weighted, as in the following model.

The Heteroscedastic Extreme Value (HEV) model [6] is the third discrete choice model considered in this paper and belongs to the RUM class as defined in formula (1). The main feature of this model, which differentiates it by the CL model and the Mixed Logit, concerns the modified assumptions on the random component. In this model, the random component, supposed distributed as a type I extreme value distribution, formula (3), is assumed independently but not identically distributed. This different hypothesis on the random component allows us to treat differently the relaxation on the IIA property with respect to the Mixed Logit model, because, in the HEV model, the homoscedasticity hypothesis of the error terms is not assumed and, therefore, different scale parameters across alternatives are estimated. This last consideration implies that cross-elasticities are not supposed to be all equals, as in the MNL and the logit models.

The main evident advantage is that the scale parameters may be defined as the weights in order to measure the uncertainty related to the alternatives and to the attributed there involved. Furthermore, the presence of large variances for the error terms influences the effects of changing of systematic utility for the generical alternative j.

Therefore, the probability for a respondent i to choose the alternative j from a choice-set C_i is:

$$P(y_i = j) = P_i(j) = \int_{\epsilon} \prod_{k \in C_i; k \neq j} \Lambda\{\frac{x'_{ij}\beta - x'_{ik}\beta + \epsilon_{ij}}{\theta_k}\} \frac{1}{\theta_j} \lambda(\frac{\epsilon_{ij}}{\theta_j}) d\epsilon_{ij} \qquad (13)$$

where 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 (2); the term $x'_{(\cdot)}\beta$ denotes the deterministic part of utility of formula (1). Note that the integral function is defined on the domain $[-\infty, +\infty]$ of the random component ϵ related to the unit i and the alternative j.

The theoretical framework of these three discrete choice models allows us to outline useful comparisons when evaluating the farmers preferences. Furthermore, the CL model is seen as the basic and simple model which does not take care of respondent's heterogeneity due to baseline variables (such as age of respondent); thus, heterogeneity is modelled in the Mixed Logit through the mixing term, $g(\psi \mid \Phi)$, where the expressed preference of respondent i, $(L_i(j))$, is measured conditioning to the personnel characteristics (ψ_{ij}).

The HEV model is considered as a further and different improvement to the CL model with respect to the Mixed Logit model. In this case the farmer 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 heteroscedasticity of the error term.

It's not straightforward matter to say that the HEV and the Mixed Logit models could be considered as competitive models in order to identify and to measure the presence of an over-dispersion when modeling the consumer preferences, with respect to the CL model.

In what follows, the farmer preferences are evaluated by considering respondent's heterogeneity or the heteroscedasticity of the alternatives.

The discrete choice models are evaluated through the following goodness-of-fit criteria: the maximum gradient element, the number of iterations to reach convergence, the Likelihood Ratio (LR), the Akaike's index (AIC) and the McFadden's LR index (McFadden LRI), bounded in $[0, 1]$, which is defined as the complementary to one of the LR.

5 Data and Variables Description

The case-study involved 137 plant nursery farms [4], 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 different situations 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, technical and economic characteristic of the electrical one. Each situation corresponds to a single choice-set formed by alternative versions of the three vehicles. The choices are defined by considering realistic baseline technical and economical attribute for biofuel and gasoline tractors while for RAMses, a prototype not yet available on the market, hypotetical versions with different levels of the key attribute have been considered. It is pointed out that the response variable is defined as the choice of one of the three alternatives.

The attributes (Table 1), each at three levels, involved in the experiment are: Price- purchasing price of the vehicle, Cost- monthly cost or operating cost, power, emissions and noise level. The background questionnaire was composed by three main sections. The first part includes questions to explore demographic and socioeconomic characteristics of the farmer/respondent; the second part is dedicated to environmental attitude of the farmer; this section include stated preferences to forecast respondent's attitude toward the electrical tractor purchase.

Table 1. Attributes description

Attribute	levels	range
Price (euro)	19,700;35,000;40,000	[19,000-40,000]
Cost (euro)	108,00;280,00;357,00	[100,00-360,00]
Power (KW)	12.00;17.70;66.00	[12.00-66.00]
Emissions (Kg/h)	0;3.60;7.20	[0-7.20]
Noise	low;medium;high	

In the third part respondents were asked to provide detailed information about the farm structure to investigate farm typology and characteristics.

With respect to the farm's characteristics and the background questionnaire, we considered: age of farmer/respondent (Table 2); farm size (Table 3); Q54 - amount of farm machinery investments (Table 4); Q21- family-run farm (Table 5); Q24- farm equipped with electrical vehicles for people transportation (Table 6); Q61- Acceptance: the stated interest in purchasing a multi-functional electric vehicle recharged by a photovoltaic system (PV) (RAMses prototype) (Table 7); Q42-relates to farms adopting good environmental practices (Table 8).

Table 2. Distribution of farmers by age; missing values:16

Years (in class)	freq.(n)	%
≤ 40	36	29.75
$41 \dashv 55$	56	46.28
> 55	29	23.97
Total	121	100.00

Table 3. Distribution of farms by size; missing values:10

Farm size (class in hectare)	freq.(n)	%
≤ 1	5	29.75
$1 \dashv 4$	64	46.28
> 4	58	23.97
Total	127	100.00

Table 4. Q54-Distribution of farms by investments; missing values:3

Inv. (class in euro)	freq.(n)	%
$\leq 100,000$	50	37.31
$100,000 \dashv 500,000$	79	58.96
$> 500,000$	5	3.73
Total	134	100.00

Two constants are created in order to analyse the choice preferences between: i) RAMses and bio-fuel (const-B); ii) RAMses 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 range autonomy are implicit. In addition, the related dummies are computed for each explicative variable; for example, by considering the farm size and the amount of farm machinery investments, three classes and six dummies are created. More specifically, when considering each of the three classes of the variable investment, two dummies are

Table 5. Q21-Family-run farm; missing values:0

Family-run	freq.(n)	%
Yes	110	80.29
No	27	19.71
Total	137	100.00

Table 6. Q24-Presence/absence on the farm of electrical vehicles for transporting people; missing values:0

El. vehicle	freq.(n)	%
Presence	125	8.76
Absence	12	91.24
Total	137	100.00

Table 7. Q61-Interest in purchasing an electrical vehicle; missing values:0

Interest	freq.(n)	%
Yes	81	59.12
No	56	40.88
Total	137	100.00

Table 8. Q42-adopting good environmental practices; missing values:0

Env. pract.	freq.(n)	%
Yes	96	70.07
No	41	29.93
Total	137	100.00

created (namely, investment-B and investment-C for the class $< 100,000 euro$), 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.

The statistical analysis has begun by evaluating firstly the conditional logit model, further heteroscedasticity of alternatives and heterogeneity of respondents are taken into account through the HEV and Mixed models, respectively. Nevertheless, statistical results do not reveal the presence of heterogeneity with respect to farms' characteristics which may have a potential effect on purchasing electrical vehicle, e.g RAMses; on the contrary, as detailed in the following (Section 6), the model results show a significant presence of heteroscedasticity across alternatives, due to the difficulties of respondent to choose between RAMses and the bio-diesel tractor or between RAMses and the diesel tractor.

Therefore, in the next section, we show the more interesting results obtained by applying the HEV model.

6 Model Results

For each estimated model, 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.

The results of the choice-experiment have been analyzed by considering also the results of the background questionnaire in order to forecast the behaviour of potential consumer classes based on individual characteristics and on the farm typology.

The first estimated HEV model, illustrated in Table 9, includes: const-B and const-C, Q54 (by conditioning to the class of farm investment machinery below 100,000 euro), Q42 referring to farms adopting good environmental practises and the operating cost level(monthly cost variable) including battery replacement. The const-B coefficient shows a propensity to purchase the bio-fuel version of the tractor, and the const-C coefficient shows greater propensity towards the electric tractor. In both constants the utility towards electrical tractor is positively influenced by the coefficients related to Q42 and negatively influenced by Q54. The estimated coefficient for the monthly cost shows a decreasing utility for the electrical vehicle as the cost increases in function of technology sets. In Table 10 the results relating to the second estimated HEV model are reported; variables and attributes involved therein are: const-B and const-C, Q21 (family farms), Q54 and the purchase price of the tractor. The estimated coefficients relating to const-B and const-C show a propensity towards bio-fuel tractor in const-B and electric tractor in const-C. Coefficients estimated for the family farms (Q21) report great propensity for buying electric tractor; while the estimated coefficients for the farms with the lowest machinery investment level show a propensity for the bio-fuel and the diesel version of the tractor, Q54-B and Q54-C respectively. The purchase price is negatively correlated with RAMses: as the price increases the utility of electric tractor decreases. The propensity toward electrical tractor utility is positively influenced by the respondents electric vehicle acceptance as revealed by question Q21 and Q42, and by the highest monthly cost differences between tractor alternatives. These cost differences are determined by hypothetical differences in electric tractor technology (battery cost and the battery life). Nevertheless, the electrical tractor utility is negatively influenced by the price and by the lowest monthly cost difference among alternatives. The model forecasts the propensity of purchasing tractors by considering tractor technical and environmental characteristics, price and then fuel type. The price sensitiveness is highly influenced by the tractor technology version. The results show also there is respondent's propensity to select the tractor version with higher level of both environmental and technical characteristics, preferences are in fact accorded to the alternative with the stronger engine power associated with the higher level of environmental attribute. The choice experiment shows that for the electrical version the premium price ranges from 1,000 to 5,000 euro; no WTP for premium price of 15,000 euro is accounted for electrical tractor. As to monthly cost, WTP shows a range from 250.00 to 290.00 euro per month, while no WTP is

Table 9. HEV model results: monthly cost and environmental characteristics

Coefficient	estimate	std.err.	p-value
const-B	6.678	1.081	<.0001
const-C	-2.138	1.820	0.2401
Q42-B	-0.941	0.684	0.1693
Q42-C	-2.094	0.509	<.0001
Q54-B	0.586	0.374	0.1175
Q54-C	0.794	0.419	0.0579
Cost	-0.032	0.005	0.0420
Scale-3	1.112	0.547	0.0420

Table 10. HEV model results: price of vehicle and environmental characteristics

Coefficient	estimate	std.err.	p-value
const-B	8.874	1.447	<.0001
const-C	-1.276	0.668	0.0561
Q21-B	-1.190	0.374	0.0015
Q21-C	-0.599	0.426	0.1589
Q54-B	0.641	0.359	0.0740
Q54-C	0.739	0.386	0.0557
Price	-4.5e-4	7.9e-5	<.0001
Scale-3	1.382	0.803	0.0853

revealed when the monthly cost reaches 350.00 euro per month. The WTP for enhancing technology sets in relation to power of the engine ranges from 55.00 to a maximum of 211.00 euro per Horsepower. The results obtained through the application of Mixed Multinomial Logit models do not reveal a presence of significant over-dispersion due to respondents' heterogeneity with respect to farms' characteristics influencing the propensity towards RAMses. This result may also be explained by considering the investigated population, which is composed by all the plant nursery farms located in a small geographical area, with very similar characteristics. Therefore, by considering the two general sources of variability, e.g. respondents and/or alternatives (Section 4), this study reveals a significant variability during the decision process, when respondents must express their preference and therefore when they must decide among the alternatives (vehicles). In fact, as reported in Table 1 and Table 2, the applied HEV models show significant scale-3 parameters; a further confirmation of the higher variability when respondents have to express a choice between the RAMses and diesel vehicles.

7 Final Remarks

In this paper, choice experiments and multinomial choice models are applied in order to evaluate the preferences of farmers towards a renewable-energy powered tractor. This preliminary work shows that there is a potential demand for electric tractor in agriculture and that the problem of the electric agricultural machinery diffusion in agriculture doesn't meet the concern about recharging infrastructure. The statistical analysis shows that there is farmers' general propensity toward environmental attribute of tractors and also acceptance and reliability for electric powered tractors. The farms with high machinery investement, the farm with low environmental impact and the farm equipped with electric vehicle for people transportation show higher attitude toward the electrical tractor. On the contrary, the family-run farms are more unwilling in purchasing the electrical version of the tractor. According to consumer survey literature, the results pointed out that the price of purchasing electrical machinery is the principal barrier to its diffusion. Electric tractor current technology (low power mainly due to battery efficiency) and the operating costs (determined by the battery cost and by its short life) are the main limits to the potential demand of the electric tractor in the nursery plant sector. Therefore the analysis underlines that there is a technology innovation need in order to allow the battery cost to fall and to increase battery life and efficiency (high power battery design). These steps are necessary to enhance the performances of the agricultural electrical tractor and to help raise its competitiveness in the market, given that battery costs have influence on tractor price and on its operating cost. It is relevant to policy makers that the diffusion of the electric machinery in agriculture, currently, asks for the implementation of supporting policy measures including price incentives in order to improve affordability of electric tractor for farmers. It must be noted also that there is a potential conflict in EU Common Agricultural Policy between fossil fuel subsidies and policy to support electric tractor diffusion in agriculture since the WTP for electric vehicle is higher when the fossil fuel price is high.

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