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Incorporating attitudes into the evaluation of preferences regarding agri-environmental practices

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Incorporating attitudes into the evaluation of preferences regarding agri-environmental practices

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Abstract

Many stated preference studies have shown that individuals' attitudes play an important role in explaining their behaviour and helping to disentangle preference heterogeneity. When responses to attitudinal questions are introduced into discrete choice models, a suitable approach that corrects for potential endogeneity must be adopted. We use a discrete choice experiment to analyse the preferences of residents regarding the use of agri-environmental practices in the peri-urban area of Milan (Italy). A detailed analysis of these preferences is relevant for policymakers as farmers on the peri-urban fringe are often asked to provide environmental services to urban-dwellers. We apply a latent class model that we extend to include indicators of individuals' attitudes towards the relationship between agriculture and the environment. Besides the application of the control function approach to deal with endogeneity, our main contribution is the use of a refutability test to check the exogeneity of the instruments in the agri-environmental setting. Our results show that attitudinal indicators help to disentangle the preference heterogeneity and that the respondents' willingness-to-pay distribution differs according to the indicators' values.

KEYWORDS: discrete choice experiment; control function; endogeneity; refutability test; individual attitudes; agri-environmental practices

JEL Classifications: C21, D91, Q12, Q24, Q51, Q57

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1. Introduction

We analyse data from a discrete choice experiment (DCE) focused on preferences regarding agri-environmental practices. Our discrete choice model (DCM) incorporates individuals' attitudes towards the relationship between agriculture and the environment.

The inclusion of attitudinal indicators in a DCM creates a potential endogeneity problem (Ben-Akiva et al., 2002). Our aim is primarily methodological, where we apply innovative solutions for this problem through the use of the control function (CF) approach with instruments defined as factors derived from a factor analysis and socio-demographic variables not introduced directly in the DCM. As our application relies on a critical assumption of the exogeneity of the instrumental variables, we also apply the overidentification test (Guevara, 2018) to test the validity of our instruments.

The incorporation of attitudes into a DCM is not an easy task. Endogeneity in classical linear regression models as well as in DCMs occurs when one or more explanatory variables are correlated with the error term. In the case of the direct inclusion of attitudinal indicators in a DCM, endogeneity may arise for two different reasons. Firstly, it can arise due to a measurement error as the indicators are functions of underlying unobserved latent construct(s) and therefore can be measured with error. Secondly, the unobserved factors are likely to be correlated with the choice; therefore, they are likely to be correlated with the corresponding error term.

From a theoretical point of view, the effect of latent attitudes in choice models creates seemingly contradictory situations. On the one hand, if there is a relevant impact of attitudes on choices, not including them in the choice model can lead to the omission of relevant variables, causing an omitted variable problem. On the other hand, their direct inclusion in the choice model may also lead to endogeneity because of the measurement error or correlation with the choice, as stated above.

Several different approaches have been adopted to incorporate the attitudinal indicators into a DCM. One of the earlier approaches consisted of the direct inclusion of the attitudinal response into the model (Boxall and Adamowicz, 2002; Greiner, 2016; Milon and Scrogin, 2006). Some authors have addressed this issue by performing a two-step analysis. In the first step, they identify homogeneous groups of respondents using the attitudinal indicators, while, in the second step, they estimate separate choice models for each group

(Aldrich et al., 2007; Castro et al., 2011; Choi and Fielding, 2013; Morey et al., 2006; Rodríguez-Ortega et al., 2016). More advanced approaches include hybrid choice models (HCMs) (McFadden, 1986; Train et al., 1987), the CF approach (Ferreira, 2010; Guevara and Ben-Akiva, 2012) and the multiple indicator solution (MIS) method (Guevara et al., 2020).

HCMs consist of a choice and a latent variable model. One or more latent variables enter the DCM as explanatory variable(s) and simultaneously act(s) as dependent variable(s) explained by observed exogenous variables. Additional equations relate the attitudinal indicators to the latent variable(s). In spite of the fact that applications of HCMs have also boomed in the environmental economics literature (Mariel et al., 2020), they are not free of modelling and estimation issues. The biggest challenge in environmental economics seems to be the use of limited sample sizes, which does not allow for a precise estimation of the usually high number of parameters of an HCM. Moreover, Chorus and Kroesen (2014) criticised the use of HCMs, given that, in some cases, instead of solving the issue of endogeneity, they can create it. In spite of the drawbacks, the use of HCMs is increasing, and they have also been applied to the analysis of farmers' and consumers' choices (Alemu and Olsen, 2019; Sok et al., 2018).

An alternative way to deal with endogeneity in the DCM is the CF approach (Ferreira, 2010; Guevara and Ben-Akiva, 2012) applied in our case study. This approach is based on the use of at least one instrument for each endogenous variable. Similarly to classical econometrics, a valid instrument must be correlated with the endogenous variable that it instruments and, at the same time, be uncorrelated with the error term of the corresponding model equation. Nevertheless, the application of the CF method in a DCM requires some additional distributional assumptions (Wooldridge, 2010, p. 587).

Given that finding valid instruments is generally a difficult task, other methods have appeared in the literature, such as the MIS. Wooldridge (2010) formalised the use of the MIS in linear models. The MIS method is applicable in specific cases in which the endogeneity is caused by the omission of a relevant variable, and there are two indicators of that omitted variable. Such indicators can in some cases be easier to collect than instrumental variables. Guevara and Polanco (2016) extended the application of the MIS in DCMs.

Mariel et al. (2018) provided the first application of the MIS in the environmental valuation literature, comparing the performance of two alternative solutions (MIS and HCM) to the endogeneity issue in a latent class framework, assuming that the omitted environmental attitude affects the class membership. Their results indicated that the MIS model leads to larger standard errors than the HCM but that the differences between the willingess-to-pay (WTP) distribution obtained by the MIS and that obtained by the HCM are not statistically significant. Thus, the MIS technique seems to be able to deal with the endogeneity issue in a simpler way than an HCM.

A comprehensive comparison of five methods to address endogeneity was presented by Guevara (2015). He compared the performance of proxy variables, the two-step CF, the CF method via maximum likelihood, the MIS and the latent variable model. Apart from the proxy variables, which correct for endogeneity only partially, the other four methods perform very well in correcting endogeneity if the assumptions implied by each method hold. The author also evaluated the performance of these five approaches if some of the assumptions fail. The results indicated that the CF with weak or with endogenous instruments results in worse performance than not addressing the endogeneity at all. The same applies to the case of the MIS with endogenous indicators. Thus, the choice of the instruments is crucial when applying both the CF and the MIS approach.

The main reason why we prefer the CF to the MIS approach is because there is no test for the suitability of the necessary indicators for the MIS approach but the assumptions of the CF approach can be tested using overidentification tests. Moreover, the MIS approach is designed to solve the endogeneity issue caused by the omission of a relevant variable, which does not apply in our study.

The results of all these approaches depend critically on the quality of the attitudinal indicators. The environmental economics literature has identified different scales to measure respondents' attitudes towards the environment. Two of the most commonly used scales are the New Environmental Paradigm Scale and the General Awareness of Consequences Scale (Stern et al., 1995). Both elicit an individual's general environmental concern. Psychometric scales are grounded in the psychological literature, and they usually consist of a set of well-defined and tested attitudinal statements with which respondents express a degree of agreement or disagreement.

It is noteworthy that psychometric scales are not always applicable. Indeed, there are some attitudes that have not yet been addressed by those scales and some contexts in which the scales from the literature are not applicable. In these situations, the use of ad hoc scales, which are developed by the researchers following precise criteria, is required. Moreover, one of the newest developments concerning the inclusion of attitudinal data in a DCM (Borriello and Rose, 2019) conclude that hypothetical localised attitudes have different effects according to the hypothetical situation.

Our study analyses respondents' preferences regarding agri-environmental practices implementable by farmers in the peri-urban agricultural area of Milan, Italy. We include in our analysis indicators of respondents' attitudes towards the relationship between agriculture and the environment. We focus on peri-urban agriculture due to its peculiarity. While peri-urban agriculture is constantly threatened by urban encroachment, urban-dwellers are increasingly interested in the recreational and ecological services potentially provided by the 'nearby' agriculture (Zasada, 2011). Our a priori hypothesis is that Milanese residents' attitudes towards the agriculture–environment relationship affect their choice preferences for sustainable agricultural practices and thus accounting for these attitudes can help to disentangle the preference heterogeneity.

The paper is organised as follows. Section 2 introduces the theoretical model, Section 3 presents the case study, Section 4 discusses the results and Section 5 concludes.

2. Methodology

2.1. Latent class model

Our baseline model is an LCM built in the form of a structural equation for the choice model and a class allocation function (Greene and Hensher, 2003). The structural equation model is grounded in the random utility theory (McFadden, 1974), which states that the utility that individual n gains from alternative j in choice set t can be decomposed into a deterministic part (V_{njt}) and a random part (ε_{njt}):

$$U_{njt} = V_{njt} + \varepsilon_{njt} = ASC_j + x'_{nit}\,\beta + \varepsilon_{nit}, \qquad (1)$$

where x_{njt} is a vector containing all the attributes of the good to be evaluated, β is the vector of the corresponding parameters and ASC_j are the alternative specific constants. One of these constants is set to zero for the sake of identification. Assuming that the random part of utility is extreme value type I distributed with location parameter zero and scale parameter one, the probability of individual n choosing alternative i in choice set t is the logit probability:

$$P_{nit} = \frac{exp(ASC_{\mathrm{i}} + x'_{\mathrm{nit}}\,\beta)}{\sum_{j=1}^{J} exp\left(ASC_j + x'_{njt}\,\beta\right)}. \tag{2}$$

In an LCM, individuals are implicitly sorted into Q classes and the analyst does not know the class to which an individual belongs. The logit probability is now conditional on belonging to class q:

$$P_{\mathrm{nit}}(\mathrm{i}|q) = \frac{exp(ASC_{\mathrm{i}} + x'_{\mathrm{nit}}\,\beta_q)}{\sum_{j=1}^{J} exp\left(ASC_j + x'_{njt}\,\beta_q\right)}. \tag{3}$$

Conditional on belonging to class q, the probability of the sequence of choices of individual n is:

$$P_n(\mathrm{i}|q) = \prod\nolimits_{t=1}^{T} P_{\mathrm{nit}}(\mathrm{i}|q) \tag{4}$$
$$= \prod\nolimits_{t=1}^{T} \left(\frac{exp(ASC_{\mathrm{i}} + x'_{\mathrm{nit}}\,\beta_q)}{\sum_{j=1}^{J} exp\left(ASC_j + x'_{njt}\,\beta_q\right)} \right).$$

The probability Ψ_{nq} of individual n belonging to class q has usually been modelled in the literature as a logit probability:

$$\Psi_{nq} = \frac{exp(\gamma_{0q} + z'_n\,\gamma_{1q})}{\sum_{q=1}^{Q} exp(\gamma_{0q} + z'_n\,\gamma_{1q})}, \tag{5}$$

where z_n denotes a set of exogenous observable characteristics of respondent n, usually socio-demographic variables, γ_{1q} is the vector of corresponding parameters and γ_{0q} are constant terms. If there are no observable characteristics of respondent n, only γ_{0q} are estimated, and the latent class probabilities will be constant across respondents for the same class. For one class, the vector of parameters γ_{1q} and γ_{0q} must be normalised to zero to ensure the identification of the model.

The unconditional probability of individual n making the sequence of choices is the sum of the conditional probabilities over the classes weighted by the probability of belonging to each class.

$$P_n = \sum_{q=1}^{Q} \Psi_{nq} \cdot P_n(\mathrm{i}|q) = \sum_{q=1}^{Q} \Psi_{nq} \cdot \prod_{t=1}^{T} P_{nit}(\mathrm{i}|q). \tag{6}$$

Therefore, the log-likelihood for the sample of N individuals is

$$LL(\beta) = ln\left(\prod_{n=1}^{N} P_n\right) \tag{7}$$
$$= \sum_{\mathrm{n}=1}^{\mathrm{N}} ln\left[\sum_{q=1}^{Q} \Psi_{nq} \cdot \prod_{t=1}^{T} P_{n\mathrm{i}t}(\mathrm{i}|q)\right].$$

The number of classes cannot be known beforehand or estimated. It is common practice to estimate the same LCM with different numbers of classes. The number of classes is then set according to a particular information criterion (AIC, AIC3, BIC or CAIC), but, as stated in the literature (Hynes et al., 2008; Scarpa and Thiene, 2005), the researcher's own judgement of the suitability of the model should also be taken into account.

2.2. Endogeneity in the allocation function of an LCM

The issue of possible endogeneity in discrete choice models is usually related to the utility equations (1) and is described by Guevara (2018, p. 243). A possible endogeneity issue in the allocation function of an LCM is almost identical to this setting because the allocation function in an LCM can be seen as an equation for a latent variable that underlies the logit probabilities Ψ_{nq} defined in equation (5). This latent variable F_{nq}, defined in equation (8), can be interpreted as the propensity to belong to class q:

$$F_{nq} = \gamma_{0q} + z_n' \gamma_{1q} + \gamma_{2q} s_n + \xi_{nq}, \tag{8}$$

where z_n is a vector of exogenous observable characteristics, s_n is an individual attitude and γ_{0q}, γ_{1q} and γ_{2q} are corresponding parameters. If there is no variable s_n in equation (8), the assumption that ξ_{nq} is extreme value type I distributed leads to the logit formula presented in equation (5), which has often appeared in the literature.

Nevertheless, there is growing environmental valuation literature describing case studies in which individual attitudes towards the valuated environmental good or service do affect individuals' preferences (Mariel et al., 2020). The inclusion of these attitudes in the allocation function therefore seems to be a necessary step in this process as the classes in an

LCM usually represent different preferences towards the valuated environmental good or service.

Let us assume that s_n is defined as

$$s_n = \alpha_0 + c_n' \alpha_1 + \eta_n, \tag{9}$$

where c_n is a vector of exogenous variables independent of the error terms ξ_{nq} and η_n and α_0 and α_1 are unknown parameters. Vector c_n can contain all or some of the exogenous observable characteristics z_n.

The underlying assumption of the allocation function logit formula (5) that has generally been applied in the literature is that $\gamma_{2q} = 0$ in (8); that is, there is no attitude influencing the allocation function. Nevertheless, if $\gamma_{2q} \neq 0$ and the term $\gamma_{2q}\, s_n$ is omitted from equation (8), it is included in a new error term $\xi_{nq}^* = \gamma_{2q}\, s_n + \xi_{nq}$; that is,

$$F_{nq} = \gamma_{0q} + z_n'\, \gamma_{1q} + \gamma_{2q}\, s_n + \xi_{nq} = \gamma_{0q} + z_n'\, \gamma_{1q} + \xi_{nq}^*. \tag{10}$$

Therefore, assuming that attitudes do affect individuals' preferences ($\gamma_{2q} \neq 0$), similarly to a classical linear regression, the endogeneity in (8) can appear for three different reasons. Firstly, if s_n is not included in (8) as an explanatory variable, its effect will be captured by a new error term ξ_{nq}^*, as defined in (10). Given that, in most cases, c_n includes at least some variables from z_n, the new error term ξ_{nq}^* will be directly correlated with z_n. The endogeneity would appear in this case due to the omission of the relevant variable (s_n). Secondly, the attitude, that is, s_n in (8), can be measured with error, and, under appropriate assumptions, endogeneity arises due to this measurement error. The third case, which is adopted and treated in detail in our case study, is the situation in which the error terms ξ_{nq} in (8) and η_n in (9) are correlated. In this case, the variable s_n in (8) is endogenous by definition.

2.3. Two-step CF approach and the refutability test

In our case study, the allocation function (8) includes typical exogenous socio-demographic variables (z_n) and an endogenous indicator (s_n) that represents the individual's attitude towards the relationship between agriculture and the environment. Given that the classes defined according to (8) will represent different preferences for the adoption of agri-environmental practices, the error terms ξ_{nq} and η_n are very likely to be correlated. For example, if, for a specific individual, the error term of the allocation function (8) is large, her/his error term of the indicator equation (9) is likely to be large too.

We apply the two-step CF approach (Guevara and Polanco, 2016) to deal with this potential endogeneity problem. Let us assume that indicator s_n is defined according to (9) and that the sets of exogenous observable characteristics in (8) and (9) coincide ($c_n = z_n$). To apply the two-step CF approach, let us assume that there are two instruments ($Instr_{1n}$, $Instr_{2n}$) available for the endogenous indicator s_n. The typical assumptions for instruments apply in this case. They need to be correlated with the instrumented variable s_n but uncorrelated with the error term ξ_{nq}. More details can be found in Guevara (2018).

In the first step of the CF approach, the indicator is regressed on the exogenous variables z_n and the two instruments:

$$s_n = \alpha_0 + z_n' \alpha_1 + \alpha_2\, Instr_{1n} + \alpha_3\, Instr_{2n} + \eta_n, \tag{11}$$

where η_n is assumed to be *i.i.d.* normally distributed. Equation (11) is estimated by ordinary least squares regression to obtain the residuals $\hat{\eta}_n$. The second step of the CF approach consists of dealing with the potential endogeneity of s_n by including $\hat{\eta}_n$ in equation (8), that is,

$$F_{nq}^{CF} = \gamma_{0q} + z_n'\gamma_{1q} + \gamma_{2q}\, s_n + \gamma_{3q}\hat{\eta}_n + \xi_{nq}. \tag{12}$$

In equation (12), the indicator s_n is expected to be no longer correlated with the new error term ξ_{nq}. Indeed, as the instruments are assumed to be exogenous and thus not correlated with ξ_{nq}, the residuals $\hat{\eta}_n$ are expected to collect in equation (12) the part of s_n that causes its correlation with the error term in (8).

The overall choice model is estimated with equation (7) and using equation (12) as an allocation function that leads to the modification of the logit probabilities defined in (5) to

$$\Psi_{nq}^{CF} = \frac{exp(\gamma_{0q}+z_n'\gamma_{1q} +\gamma_{2q}\, s_n+ \gamma_{3q}\hat{\eta}_n)}{\sum_{q=1}^{Q} exp(\gamma_{0q}+z_n'\gamma_{1q} +\gamma_{2q}\, s_n+ \gamma_{3q}\hat{\eta}_n)}. \tag{13}$$

An important condition for the application of the CF approach is that the instruments used in the first step of CF, equation (11), are exogenous. The use of more than one instrument allows for the application of the refutability test for exogeneity of the instruments (Guevara, 2018).

The test exploits the overidentification condition, and it is performed in three steps. The first two steps apply the CF approach to the choice model that potentially suffers from endogeneity. In the first step, equation (11) is estimated to obtain the residuals $\hat{\eta}_n$. In the second step, the LCM is estimated by maximising (7) and the use of (13). The value of the maximised log-likelihood is denoted by LL^{CF}. The third step re-estimates the choice model by maximising equation (7) through the use of modified equation (13), which includes all but one instrument. If only two instruments are available, equation (12) in the third step becomes:

$$F_{nq}^{CF_{instr}} = \gamma_{0q} + z_n'\gamma_{2q} + \gamma_{1q}\, s_n + \gamma_{3q}\hat{\eta}_n + \gamma_{4q}\, Instr_{1n} + \xi_{nq}. \quad (14)$$

The value of the maximised log-likelihood is denoted in this case by $LL^{CF_{instr}}$. The test statistic is defined as

$$S_{REF} = -2(LL^{CF} - LL^{CF_{instr}}) \sim \chi^2_{df}, \quad (15)$$

where the degrees of freedom (df) equal the degree of overidentification of the model (the number of instruments minus the number of endogenous variables).

The null hypothesis of the test is that the two instruments ($Instr_{1n}$, $Instr_{2n}$) are exogenous instruments, and the alternative hypothesis is that one or both instruments are endogenous. That is why the test must then be repeated for all possible combinations of the instruments.

3. Case study

3.1 Study area and attributes

The case study refers to a DCE conducted in 2018 in the Italian city of Milan. The aim of the DCE was to collect data to evaluate the preferences of the inhabitants of the municipality of Milan regarding agri-environmental practices implementable in the peri-urban area of the city. Agricultural activity in the peri-urban area of Milan is mainly concentrated in the southern and western parts, and it consists of growing rice and corn (75% of the utilised agricultural area), followed by grassland (7.5%) (Istat, 2010). Although lying on the urban fringe, agriculture in this area is intensive, rather than characterised by an agri-environmental orientation. Most of the farms engaged in the provision of ecosystem services offer recreational activities to citizens rather than environment-friendly agricultural practices. Indeed, while the former are rewarded by citizens paying for a ticket to participate in the recreational activities, the latter should be supported by public subsidies. However, given the low uptake of environment-friendly practices, it is likely that the public subsidies are not sufficiently high to compensate farmers for the income loss due to their adoption. Our focus is on the peri-urban area because, despite the low rate of adoption of agri-environmental practices, an increase in their adoption is likely to produce high social benefits due to the proximity to the city.

We consider four agri-environmental practices and their related ecological benefits that could be practiced in the peri-urban area of Milan, specifically organic farming, fast-growing tree plantations on agricultural land, field margin management and cover crops. The four practices were selected after focus group discussions involving local farmers and in consultation with experts. All four practices are already included in the current Rural Development Programme of the Lombardy region (Regione Lombardia, 2020) with a subsidy provided by local authorities to farmers for adoption of the corresponding practice. Despite the public subsidy, the four practices are currently only marginally practiced in this peri-urban area.

More detailed information about the study area and the rationale behind the selection of the four agri-environmental practices can be found in the study by Arata et al. (2020) along with a detailed description of the four practices and the related ecological benefits. The choice task format used in the survey comprises two hypothetical alternatives and one status quo alternative. Each alternative is composed of a specific level for each of the four agri-environmental practices and a level for the corresponding tax (as the cost of providing the practice). All the considered agri-environmental practices are achieved by a specific combination of attributes described in Table 1 aiming to improve the positive impact of agriculture on the environment. Similar to the attribute selection, all the attribute levels were set up after focus group discussions and expert consultations (Arata et al., 2020).

We used the Bayesian efficient design, minimising the expected *D*-error (Hensher et al., 2015; Scarpa and Rose, 2008) based on prior parameter estimates obtained from a pilot study. The generated design comprised 30 lines, which were divided into five blocks of six choice sets each. To avoid position bias, the choice set order was randomised during the survey. Before showing the first choice set, an *honesty priming* task was introduced to reduce the hypothetical bias (de-Magistris et al., 2013).

3.2 Attitudinal statements

Apart from the choice sets and the socio-demographic information, the questionnaire also contained seven statements regarding the respondent's attitude towards the relationship between agriculture and the environment. While there are well-established psychometric scales for the general attitude towards the environment and human–environment interaction (Dunlap and Liere, 1978; Ryan and Spash, 2012; Stern et al., 1995) to the best of our knowledge, there is no scale to elicit individuals' attitude towards the environment–agriculture relationship. That is why we included an ad hoc scale, developed following basic rules that come from well-established scales. First, following Dunlap and Liere (1978), who introduced a psychometric scale for the New Environmental Paradigm, we collected information on the environment–agriculture interaction from the scientific literature,

TABLE 1 Attributes' definition, positive impact on the environment and levels

Attributes	Ecological benefits	Attribute levels	Labels
Organic farming (% of the utilised agricultural area (UAA))	• Reduction in nitrogen leaching into the soil • Reduction in nitrous oxide emissions (greenhouse effect 298 times higher than carbon dioxide)	3%*	
		10%	*Org_medium*
		20%	*Org_high*
Fast-growing tree plantation (% of the UAA)	• Carbon sequestration • Refreshing and shadowing	0.5%*	
		2%	*Forest_medium*
		5%	*Forest_high*
Biodiversity strips	• Effects on the farmland bird population and on pollinators	Absent*	
		Strips sown with the main crop but treated with a reduced amount of fertilisers and pesticides	*Strips_medium*
		Strips sown with wildflowers beneficial for farmland birds and pollinators	*Strips_high*

The status quo level is denoted by *.

agricultural policy measures addressing this issue and expert consultations. This collection allowed for the development of seven attitudinal statements, presented in Table 2, which cover several crucial aspects of the environment–agriculture relationship: carbon sequestration; biodiversity; water quality; environmental pollution; air quality; and soil erosion. Following Dunlap and Liere (1978), we included statements referring to both positive and negative impacts of agriculture on the environment. Unfortunately, these statements had not been tested and validated prior to their use in our survey. To solve this problem at least partially, we performed an exploratory factor analysis to check that the underlying attitudinal constructs were properly represented by the proposed statements (Mariel and Meyerhoff, 2016; Mariel et al., 2018). The use of an ad hoc scale, in spite of being an ideal solution if no established scale is available, is common in many different fields (for example, Greiner (2016) and Wuepper et al. (2019) in agricultural economics, Márquez et al. (2020) in transportation or Boxall and Adamowicz (2002) in wilderness studies).

The respondents were asked to indicate their agreement with each of the statements using a five-point Likert scale, following Márquez et al. (2020), where the five-point scale is a good compromise to reduce the central and leniency biases of respondents (Foddy, 2001).

The order of the statements shown in the survey was not randomised. The discrete choice literature has not analysed a possible anchoring effect in the responses to attitudinal statements, but it is definitely an important point for future research.

TABLE 2 Attitudinal questions and relative frequency (%) (1 = strongly disagree; 5 = strongly agree)

		Label	1	2	3	4	5
1	Agriculture can contribute to carbon sequestration	*carbon_sequestration*	4.9	9.3	27.5	33.3	25
2	Agriculture can contribute to preserving biodiversity	*preserve_biodiversity*	1.5	4	16	37	41.5
3	Agriculture can contribute to improving water quality	*water_quality*	1.5	6.6	23	32.2	36.8
4	Agriculture pollutes the environment	*pollution*	24.4	21.5	28.2	17.3	8.6
5	Agriculture can contribute to improving air quality	*air_quality*	0.7	3.1	19.5	38.3	38.4

6	Agriculture can contribute to reducing soil erosion	*soil_erosion*	1.5	7.1	24.6	35.7	31.1
7	Agriculture contributes to biodiversity loss	*biodiversity_loss*	18.8	16.9	27.7	24	12.6

4. Results

4.1 Descriptive analysis

Through an online survey, a market research company collected a representative sample of 600 respondents from the adult population of the municipality of Milan based on their age, gender, income and residential area. After the cleaning stage, our final sample was composed of 549 valid responses, representing 3,294 observations as each respondent faced 6 choice tasks.

Table 3 shows the summary statistics of the socio-demographic variables of our final sample. The variable Income-class is based on the ratio between family income and family size (children included). The questionnaire also collected information on the number of times the respondents had visited the agricultural peri-urban area of the study in the last 12 months for leisure.

TABLE 3 Socio-demographic variables

	Mean	***St. dev.***	***Label***
Age	42.2	14.6	*age*
Male	0.52	0.5	*male*
University degree	0.46	0.5	*degree*
Middle-income class (€700–1,400/month)	0.45	0.5	*middle_income*
High-income class (>€1,400/month)	0.21	0.4	*high_income*
Employed	0.71	0.45	*employed*
Family size	2.9	1.2	*family_size*
Environmental association membership	0.13	0.34	*env*
Number of visits to the area for leisure in a year	8.03	37.9	*leisure*

Note. The following variables are dummy-coded: male = 1 if the respondent is male; university degree = 1 if the respondent holds a university degree; middle-income class = 1 if the respondent's family per capita income is between €700 and €1400/month; high-income class = 1 if the respondent's family per capita income >€1,400/month; employed = 1 if the respondent is employed; and environmental association membership = 1 if the respondent is a member of an environmental association.

Due to the online survey administration mode, the older age categories are slightly under-represented, the respondents with university degrees are slightly over-represented and employed people are under-represented compared with the general population of Milan.

In spite of these misalignments, our sample is representative of the Milanese population in terms of gender, income and residential area.

Table 2 shows the relative frequency of the scores given by the respondents to the attitudinal questions regarding the relationship between agriculture and the environment. The respondents feel that agriculture affects the environment as a clear majority of the respondents scored four or five for the statements indicating a positive influence of agriculture on the environment (carbon sequestration, preserving biodiversity, water quality, air quality and soil erosion) and approximately one-quarter of the respondents indicated a negative influence of agriculture on the environment, scoring four or five for the pollution and biodiversity loss sentences.

Table 4 presents the pairwise correlation coefficients between the seven attitudinal responses. The positive correlation coefficient between each pair of the five statements indicating a positive impact of agriculture on the environment (*carbon_sequestration*, *preserve_biodiversity*, *water_quality*, *air_quality* and *soil_erosion*) confirms the general consistency in the responses across the statements. The statements related to *pollution* and *biodiversity_loss* represent a negative impact of agriculture on the environment. Apart from representing a negative impact of agriculture, the statements for *biodiversity_loss* and *pollution* use different wording from the positive impact statements as the word ‘can’ is omitted. In addition, the *pollution* statement is intended to capture a ‘general’ link between agriculture and the environment contrary to the specific interactions of the other statements. As expected, the correlation matrix shows a large correlation between these two negative statements while there is a small correlation with the others.

TABLE 4 Correlation matrix of the responses to the statements

	Carbon sequestration	*Preserve biodiversity*	*Water quality*	*Pollution*	*Air quality*	*Soil erosion*	*Biodiversity loss*
carbon_sequestration	1.00	0.32	0.29	0.22	0.36	0.37	0.34
preserve_biodiversity	0.32	1.00	0.64	-0.09	0.59	0.49	-0.02
water_quality	0.29	0.64	1.00	-0.02	0.58	0.44	0.01
pollution	0.22	-0.09	-0.02	1.00	-0.07	<0.01	0.56
air_quality	0.36	0.59	0.58	-0.07	1.00	0.55	-0.01
soil_erosion	0.37	0.49	0.44	<0.01	0.55	1.00	0.14
biodiversity_loss	0.34	-0.02	0.01	0.56	-0.01	0.14	1.00

4.2 Empirical Model

The structural equation of our model corresponding to equation (1) is specified as:

$$\begin{aligned} V_{nit} = ASC_i \quad & + \beta_{org_{medium}} org_{medium_{nit}} + \beta_{org_{high}} org_{high_{nit}} \\ & + \beta_{forest_{medium}} forest_{medium_{nit}} + \beta_{forest_{high}} forest_{high_{nit}} \\ & + \beta_{strips_{medium}} strips_{medium_{nit}} + \beta_{strips_{high}} strips_{high_{nit}} \\ & + \beta_{covercrops} covercrops_{nit} + \beta_{cost} cost_{nit}, \end{aligned} \tag{16}$$

where org_{medium}, org_{high}, $forest_{medium}$, $forest_{high}$, $strips_{medium}$, $strips_{high}$, $covercrops$ and $cost$ represent the attribute levels presented in Table 1. That means that all the attributes except for $cost$ are dummy coded to allow for a possible non-linear effect.

The class allocation function corresponding to equation (8) is defined in our model as:

$$\begin{aligned} F_{nq} = \gamma_{0q} + \gamma_{1q} age_n + \gamma_{2q} male_n + \gamma_{3q} degree_n + \gamma_{4q} middle\_income_n \\ + \gamma_{5q} high\_income_n + \gamma_{6q} employed_n + \gamma_{7q} family\_size_n \\ + \gamma_{8q} carbon\_sequestration_n + \xi_{nq}, \end{aligned} \tag{17}$$

where all the right-hand side variables are presented in Table 2 and Table 3. The reason for the inclusion of one attitudinal statement – $carbon\_sequestration$ – in the class allocation function lies in the potential influence that the individual attitude towards the relationship between agriculture and the environment can have on the individual class allocation. Given that this additional explanatory variable, represented by the first statement presented in Table 2, is endogenous by definition, as the errors in (8) and (9) are expected to be correlated, we applied the CF approach to estimate the above-defined model consistently.

We needed to find appropriate instruments for the auxiliary equation defined in (11). The instruments must be related to the instrumented variable ($carbon\_sequestration$) but uncorrelated with the error term ξ_{nq} in the allocation function defined in (8). Given this theoretical setting, the first instrument that we used is the dummy variable indicating whether the individual is a member of an environmental association (*env*). The second instrument is the variable representing the number of times the respondent visited the area under study in the last 12 months for leisure (*leisure*). To increase the number and quality of the instruments, we used two additional instruments extracted from the exploratory factor analysis, called $factor$ 1 and $factor$ 2. The auxiliary equation (11) then becomes

$$s_n = \alpha_0 \ + \alpha_1 age_n + \alpha_2 male_n + \alpha_3 degree_n + \alpha_4 middle\_income_n + \alpha_5 high\_income_n + \alpha_6 employed_n + \alpha_7 family\_size_n + \alpha_8 \ env_n + \alpha_9 \ leisure_n + \alpha_{10} \ factor1_n + \alpha_{11} \ factor_n + \eta_n. \quad (18)$$

Apart from $carbon\_sequestration$, we collected six additional statements, presented in Table 2, and used them to form instruments for the auxiliary equation (11). These instruments are defined as the main two factors obtained from an exploratory factor analysis applied to these six statements. The main results of this factor analysis are presented in Table 5.

It seemed reasonable to choose a two-factor solution, as the percentage of variance explained decreases sharply with the third factor. Moreover, the first two factors represent more than 70% of the total variance. The high factor loadings of Factor 1 on the statements related to *preserve_biodiversity*, *water_quality*, *air_quality* and *soil_erosion* are in line with the information obtained from the correlation matrix presented in Table 4 as they underline how these statements represent positive and specific impacts of agriculture on the environment. The second factor, with high factor loadings for *pollution* and *biodiversity_loss*, represents the negative impact of agriculture and is once more in line with our finding shown in Table 4, showing how these statements are related to more general aspects of the impact of agriculture on the environment.

TABLE 5 Exploratory factor analysis

Eigenvalues and percentages				**Factor loadings**		
Factor	*Eigenvalue*	*% Variance*	*Cumulative %*	**Statement**	*Factor 1*	*Factor 2*
Factor 1	2.65	44.28	44.28	*preserve_biodiversity*	0.79	-0.07
Factor 2	1.57	26.25	70.53	*water_quality*	0.76	-0.03
Factor 3	0.60	10.03	80.57	*pollution*	-0.05	0.56
Factor 4	0.42	7.10	87.66	*air_quality*	0.77	-0.05
Factor 5	0.39	6.47	94.13	*soil_erosion*	0.64	0.11
Factor 6	0.35	5.87	100.00	*biodiversity_loss*	0.05	0.99

Similar to $carbon\_sequestration$, the responses presented in Table 2 to statements 2 to 7 are endogenous by definition and cannot be used directly as instruments. Nevertheless, the two factors that can be extracted from the factor analysis represent specific underlying attitudinal constructs that can be unrelated to the error term in the allocation function. To verify the exogeneity of these two artificially created instruments together with the other two instruments *env* and *leisure*, we applied the refutability test (Guevara, 2018).

4.3 Estimation results

This section presents the estimates of a plain LCM and an LCM that includes the potentially endogenous variable *carbon_sequestration* in the allocation function (LCM with indicator). The main reason for the estimation of the plain LCM is to serve as a benchmark for the CF approach applied to the LCM with indicator. The number of classes of the two LCMs were set according to several information criteria. TABLE presents these criteria for the LCM with an indicator, but the figures for the plain model were very similar and led to the same conclusion. While the AIC and BIC support a four-class model, the CAIC supports a two-class model. The four-class model presents a partial overlap of classes, while, in the two-class model, the interpretation of the two classes is straightforward. As discussed by Scarpa and Thiene (2005) and Hynes et al. (2008), the choice of the number of classes needs to be tempered by the researcher's own judgement of the model's suitability, hence we chose the two-class model. The estimates of the three-class and four-class LCM are reported in Appendix A (on-line).

TABLE 6 Information criteria for the LCM with an indicator

	2 classes	**3 classes**	**4 classes**
LogL	-2825.8	-2749.3	-2645.4
Number of parameters	30	50	70
Sample size	3294	3294	3294
AIC	5711.6	5598.6	5430.8
BIC	5894.6	5903.6	5857.8
CAIC	5924.6	5953.6	5927.8

The first block of estimates in Table 7 presents the estimation of the plain LCM, which includes in the allocation function only socio-demographic variables and no indicator. The ASC coefficients are positive and significant in both classes, indicating that, on average, individuals move away from the status quo option. All the coefficients associated with the rise in the adoption of agri-environmental practices are positive and significant in both classes. This indicates that individuals are positively affected by an increase in the level of each non-cost attribute. What constitutes the main difference between the two classes is the tax coefficient and, subsequently, the WTP for each attribute. The WTP for improving the adoption of agri-environmental practices in the peri-urban area of Milan in class 2 is approximately five times higher than that in class 1. The parameter estimates of the class allocation equation indicate that the middle- and high-income levels, being male and having a larger family size increase the probability of belonging to class 2, which is characterised by higher WTP values.

The second block of estimates in Table 7 present the estimation of the LCM with an indicator. There are therefore two additional variables in the allocation function. The first one is the *carbon_sequestration* indicator itself, and the second one contains the residuals from the auxiliary regression defined in equation (11).

The estimates of the corresponding auxiliary regression (18) are represented in Table 8. It shows that two out of the four instruments (factors obtained from the explanatory factor analysis) are highly correlated with the instrumented variable (*carbon_sequestration*), apart from *degree* and *male*.

An important point to notice is that the variable s_n in (18) is assumed to be a continuous variable as the error term in (11) and (18) is assumed to be normally distributed. Nevertheless, our variable s_n is measured on a Likert scale. The discussion regarding whether a five-point Likert scale can be used as an approximation for an underlying continuous variable is not new in the literature. There has, however, not been much discussion of this topic in the context of discrete choice models. One exception is Guevara (2015, pp. 248 and 251), who analysed the impact of using discrete indicators instead of continuous indicators to represent the underlying latent construct in a very similar context to ours. The author performed Monte Carlo simulations and showed that the use of discrete indicators when the latent variable is continuous and a linear model is applied produces the expected results, which are very similar to those obtained by applying continuous indicators[3].

The comparison of the utility coefficients of the two blocks of estimates in Table 7 leads to the conclusion that the inclusion of the indicator in the allocation function does not have an important impact. Nevertheless, the coefficients of the class allocation function present noteworthy differences.

[3] We also estimated an ordered logit auxiliary regression to account for the discrete character of the indicator and found that the results are not affected. The results from this estimation are reported in Table B.2 and Table B.3 in the Appendix B.

Table 7. Estimation of the LCMs

	Plain LCM			LCM with indicator		
	Estimate	p-value		Estimate	p-value	
Parameter of the utility equation						
Class 1						
ASC1	0.27	0.34		0.30	0.25	
ASC2	0.55	0.04	**	0.59	0.02	**
tax	-0.10	0.00	***	-0.10	0.00	***
organic medium	0.73	0.00	***	0.68	0.00	***
organic high	0.51	0.03	**	0.45	0.04	**
forest medium	0.53	0.01	***	0.48	0.01	***
forest high	0.66	0.00	***	0.62	0.00	***
strips medium	0.49	0.02	**	0.47	0.02	**
strips high	0.41	0.05	**	0.40	0.05	**
cover crops	0.70	0.00	***	0.69	0.00	***
Class 2						
ASC1	1.42	0.00	***	1.45	0.00	***
ASC2	1.48	0.00	***	1.51	0.00	***
tax	-0.02	0.00	***	-0.02	0.00	***
organic medium	0.30	0.00	***	0.30	0.00	***
organic high	0.61	0.00	***	0.62	0.00	***
forest medium	0.33	0.00	***	0.33	0.00	***
forest high	0.47	0.00	***	0.48	0.00	***
strips medium	0.28	0.00	***	0.28	0.00	***
strips high	0.54	0.00	***	0.55	0.00	***
cover crops	0.33	0.00	***	0.33	0.00	***
Parameter of the class 2 allocation equation						
constant	0.25	0.32		-2.05	0.00	***
age	0.00	0.20		-0.01	0.08	*
degree	-0.22	0.03	**	-0.37	0.00	***
occupied	-0.01	0.94		-0.10	0.34	
Family size	0.13	0.01	***	0.11	0.02	**
middle income class	0.18	0.10	*	0.19	0.08	*
high income class	0.71	0.00	***	0.79	0.00	***
male	0.35	0.00	***	0.27	0.00	***
carbon sequestration				0.80	0.00	***
residuals from auxiliary regression				-0.70	0.00	***
LogLik	-2833.9			-2825.8		
N	3294			3294		
K	28			30		
AIC	5722			5710		
BIC	5892.8			5893		
CAIC	5920.8			5923		

*,**, *** indicate 10%, 5%, 1% significance level respectively

First, it is worth noting that the coefficient associated with the residuals is significant, indicating that the *carbon_sequestration* indicator is indeed endogenous. Second, the indicator coefficient is also positive and significant. This highlights the fact that individuals' attitudes towards the role of agriculture in favouring carbon sequestration matters in the class allocation and has a positive impact. A higher score for that indicator increases the probability of belonging to class 2. This is in line with the result that the WTP values for increasing the adoption of agri-environmental practices in the peri-urban area of Milan are higher in class 2. Class 2 is therefore characterised by an attitude of favouring a stronger positive link between agriculture and the environment than class 1.

TABLE 8 Estimates of the auxiliary regression

	Estimate	*p-value*	
Constant	3.34	<0.00	***
Factor 1	0.49	<0.00	***
Factor 2	0.34	<0.00	***
Environmental NGO member	-0.04	0.76	
Number of visits for leisure	0.03	0.73	
Age	0	0.11	
Degree	0.21	0.02	**
Occupied	0.04	0.67	
Family size	-0.02	0.59	
Middle-income class	-0.05	0.63	
High-income class	-0.09	0.49	
Male	0.14	0.09	*

The above-stated results are only valid if the four instruments used in the estimation are exogenous. The null hypothesis of the refutability test is that all the instruments included in equation (11) are exogenous, while the alternative hypothesis is that at least one of those instruments is not. As the refutability test requires the estimation of the class allocation equation with all but one instrument, the choice model was estimated four times, each time excluding one of the four instruments in the class allocation equation. The *p*-values of the refutability test in all four cases are greater than 0.49, leading to non-rejection of the null hypothesis. Hence, all four of our instruments are exogenous.

To show the impact on the estimation results of the selection of the indicator and of the instruments derived from the factor analysis, we present the estimation of the allocation functions and of the auxiliary regressions of additional six models in Table B.1 in the Appendix. In each model, a different statement listed in Table 2 is included as an indicator in the allocation function. Thus, for each model, we first ran the factor analysis on all the statements except the one used as indicator and then we applied the CF approach. Finally, we conducted the refutability test on the four instruments used. As the refutability test must be performed for different combinations of the four instruments, in Table B.1 we present only the lowest of the four p-values corresponding to each combination. As can be seen, if the *carbon_sequestration* indicator is not included in the allocation function but enters the factor analysis (as happens when a statement different from *carbon_sequestration* is employed in the allocation function), the exogeneity of the instruments is rejected at the 5% level for all but one model that shows a p-value equal to 0.08. This highlights the enormous impact of the carbon_sequestration indicator on the factor analysis results, implying the loss of exogeneity of the artificial instruments.

Finally, we computed the WTP values of Milanese citizens for increasing the adoption of each agri-environmental measure using the results presented in Table 7. The class WTP values for a marginal improvement in one of the measures were computed as the negative ratio between the parameter estimate associated with that measure and the parameter estimate associated with the cost. The individual WTP values were obtained as the weighted average of the class WTP values, for which the weights were set by the class allocation function. Considering, for example, the WTP of individual n for increasing the adoption of organic farming from the current level to the medium level and assuming the existence of two classes, according to equations (3) and (5):

$$WTP_{n,org\_medium} = \Psi_{n1}\left(-\frac{\beta_1^{org\_medium}}{\beta_1^{cost}}\right) + \Psi_{n2}\left(-\frac{\beta_2^{org\_medium}}{\beta_2^{cost}}\right). \qquad (19)$$

Table 10 shows the mean, median and standard deviations of the estimated distribution of individuals' WTP values corresponding to the plain LCM and the LCM with an indicator. The descriptive statistics are very similar in the two models. The highest mean WTP is for promoting the adoption of organic farming up to 20% of the UAA in the peri-urban area of Milan, followed by supporting biodiversity strips. Cultivating field strips with the main crop but with reduced amounts of fertilisers and pesticides (*biodiversity strips: medium*) seems to be the least interesting measure for the inhabitants of Milan as the mean WTP is the lowest.

TABLE 9 Descriptive statistics of the estimated population variation of the WTP values

	Plain LCM			**LCM with an Indicator**		
	Mean	*Median*	*St. dev.*	*Mean*	*Median*	*St. dev.*
Organic farming: medium	13.91	13.94	0.53	14.16	14.25	1.02
Organic farming: high	26.08	26.17	1.65	26.62	26.89	3.14
Fast-growing tree plantation: medium	14.47	14.51	0.72	14.94	15.07	1.42

Fast-growing tree plantation: high	20.57	20.63	1.1	21.20	21.39	2.11
Biodiversity strips: medium	12.47	12.50	0.60	12.72	12.82	1.13
Biodiversity strips: high	23.06	23.14	1.48	23.54	23.79	2.78
Cover crops	15.11	15.15	0.65	15.22	15.33	1.15

Given that the estimated population WTP distributions for all the attributes presented in Table 9 seem to overlap, showing no big differences between the plain LCM and the LCM with an indicator, we investigated whether the sample variation of the WTP estimates for specific values of the socio-demographic variables presents some differences. To compute the sample variation of WTP, we considered the uncertainty of all the parameter estimates involved in the computation of the WTP. We simulated the distribution of all the parameters involved in the computation of the WTP values defined by (19) with the use of the estimations presented in Table 7. The values of the socio-demographic variables in the class allocation function were set to median values (*age* = 42, *degree* = 1, *employed* = 1, *family size* =3, *middle-income class* = 1, *high-income class* = 0, male = 1 and *carbon sequestration* = 4). Table 10 presents the sample distribution of the WTP values of the plain LCM and of the LCM with an indicator. Their difference was tested using the complete combinatorial test (Poe et al., 2005). Similarly to the results in Table 9, the equality of the distribution (null hypothesis) was not rejected for any attribute; hence, we cannot reject the hypothesis that the WTP estimates of the plain LCM are statistically different from the WTP estimates of the LCM with an indicator.

TABLE 10 Descriptive statistics of the sample variation of the WTP values

	Plain LCM	**LCM with an indicator**	**Poe test**
	Expected value	*Expected value*	*p-value*
Organic farming: medium	13.94	14.51	0.55
Organic farming: high	26.18	27.72	0.57
Fast-growing tree plantation: medium	14.51	15.43	0.58
Fast-growing tree plantation: high	20.63	21.93	0.57
Biodiversity strips: medium	12.50	13.12	0.55
Biodiversity strips: high	23.15	24.50	0.58
Cover crops	15.15	15.64	0.53

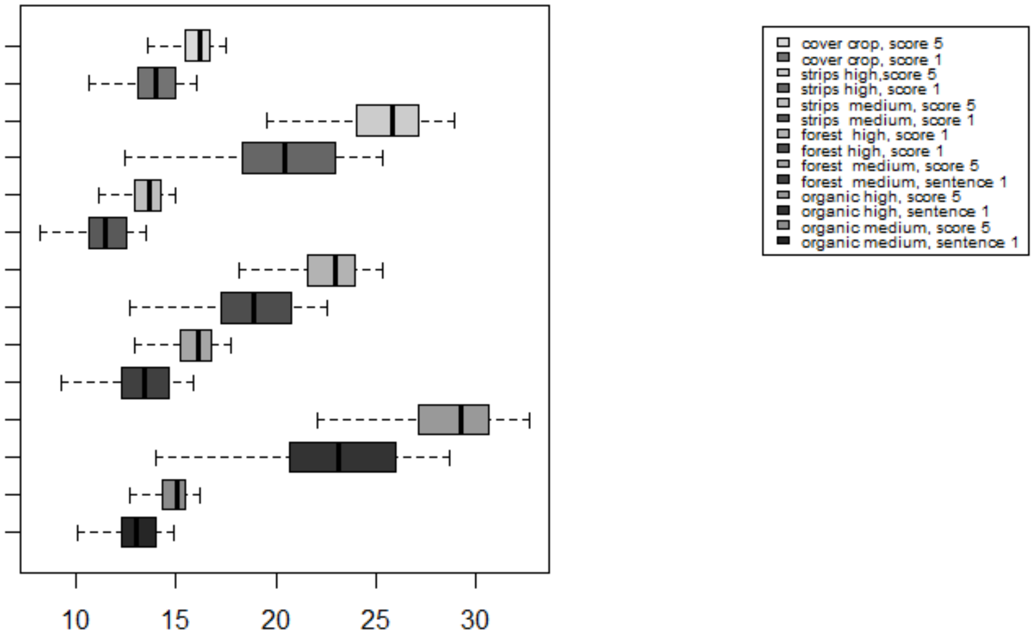
Given that the WTP distributions in Table 9 and Table 10 are very similar, the inclusion of the indicator in the model does not seem to have a strong impact on the overall distribution of individuals' WTP. Nevertheless, the inclusion of the indicator can be useful in disentangling the preference heterogeneity. That is why, in Table 11, we present individuals' WTP distributions separately for the people who gave the highest scores for the *carbon_sequestration* indicator (i.e. they strongly agree with the statement 'Agriculture can contribute to carbon sequestration') and for the people who gave the lowest scores for that indicator.

TABLE 11 Descriptive statistics of the WTP distribution by indicator scores

	Low-score people (score = 1)			**High-score people (score = 5)**		
	Mean	*Median*	*St. dev.*	*Mean*	*Median*	*St. dev.*
Organic farming: medium	12.93	13.03	1.31	14.87	15.02	0.79
Organic farming: high	22.82	23.19	4.05	28.83	29.28	2.44
Fast-growing trees plantation: medium	13.22	13.39	1.82	15.94	16.14	1.10
Fast-growing trees plantation: high	18.64	18.86	2.71	22.67	22.98	1.64
Biodiversity strips: medium	11.36	11.47	1.45	13.51	13.67	0.88
Biodiversity strips: high	20.18	20.46	3.56	25.47	25.87	2.15
Cover crops	13.83	13.94	1.48	16.02	16.19	0.89

The value of the indicator clearly influences the allocation function and therefore the probability of belonging to a specific class. According to Table 11, the mean of the individuals' WTP of the high-score people is approximately 20% higher than the mean of the low-score people. Figure 1 shows the WTP distributions for these two categories of individuals and provides a straightforward visual comparison. As can easily be seen, the WTP distributions for these two subgroups do not heavily overlap on any of the attributes. To test the equality of the two distributions for each attribute, we employed the complete combinatorial test (Poe et al., 2005). In all seven attribute comparisons, the null hypothesis of equality was rejected at the 10% significance level, which seems to be a reasonable significance level given the relatively limited sample size. This means that the inclusion of the indicator helps to disentangle the preference heterogeneity and that its inclusion can aid in understanding the respondents' behaviour.

FIGURE 1 WTP distribution of people scoring 5 and people scoring 1 for the carbon sequestration indicator



5. Conclusions

This study investigated the preferences of Milanese residents regarding agri-environmental practices implementable in the peri-urban area of Milan. The analysis was carried out by applying an LCM that includes in the allocation function individuals' attitude towards the relationship between agriculture and the environment. More specifically, we considered the level of agreement of the respondents to the statement 'Agriculture can contribute to carbon sequestration'. We addressed a possible endogeneity issue caused by the inclusion of this attitude indicator by using the CF approach, and we tested the exogeneity of the instruments used in the CF approach with the refutability test. Our results show that the responses to an attitudinal statement contribute significantly to explaining the class allocation of the respondents and therefore lead to a better understanding of the preference heterogeneity. The CF approach also shows that, in our study, the attitudinal indicator is endogenous; therefore, including it without correcting for endogeneity would lead to biased parameter estimates.

If attitudes affect the choice behaviour considerably and are omitted from the model, the parameter estimates can be inconsistent. In our study, the mean and standard deviations of the WTP distribution are not largely affected by the inclusion of the individuals' attitudes in the choice model. This is in line with the literature, which shows that even more complicated models, including attitudinal constructs such as an HCM, result in a WTP distribution that is not significantly different from the WTP distribution of a model without attitudinal variables (Mariel and Meyerhoff, 2016; Mariel et al., 2015, 2018; Taye et al., 2018).

One possible reason for that result may be the definition of the scales used to collect the attitudinal indicators. Well-established scales from the psychological literature to elicit the general attitude of an individual towards the environment may be suitable in some situations but not in others. In addition, in some fields, like the one in this study concerning the agriculture–environment relationship, no well-established scales have so far been proposed and tested in the literature. In these cases, researchers usually use ad hoc statements. This was also the case in our study. However, we set up the scale following the best practices available in the literature on psychometric scales and performed some internal validation through the use of factor analysis. Future research should include previously tested psychometric scales. Consequently, more research is needed to investigate the bridge between the psychological literature and the economic evaluation studies to produce valid measures of individual attitudes in different contexts. In line with Borriello and Rose (2019), future research should distinguish between general and specific localised environmental attitudes.

In spite of the overlap of the WTP distributions of a model with and a model without an attitudinal indicator, the incorporation of the indicator into the choice model allowed us to analyse the WTP distributions according to the value taken by the indicator. Indeed, in our study, the WTP distribution differed significantly according to the individuals' attitudes: individuals who gave high scores to the carbon sequestration statement presented a higher WTP for all the agri-environmental practices considered.

As we corrected for endogeneity in our LCM through the CF approach, we used four different instruments with very diverse natures. Our choice of the instruments is innovative for two reasons. Firstly, two of our instruments are factors derived from a factor analysis of six attitudinal statements eliciting the respondents' attitude towards the relationship between agriculture and the environment. These statements were collected in the same way as the instrumented indicator; therefore, the two factors derived from them are likely to be related to that indicator. We applied the refutability test to check their exogeneity. Secondly, the other two instruments that we employed were socio-demographic variables that were not introduced directly into the allocation function. This raises the idea of introducing innovative socio-demographic variables into future surveys that can be used as instruments of the attitudinal indicators.

Peri-urban agriculture surrounds the city, and this offers some advantages in terms of a local policy oriented towards supporting agri-environmental practices. First, the policy implementation is easier to control. Second, given the proximity to the urban centre, urban-dwellers can benefit more from the positive environmental effects of those practices. Third, the concentration of the potential adoption of agri-environmental practices in the same limited area is likely to amplify the total effect. The influence that an individual's attitude can have on his or her WTP for an environmental good provided by agriculture has important implications for planning a local agricultural policy. Despite the fact that, in the EU, the agricultural policy is defined at the EU level, with some degree of decision making about the implementation of environmentally friendly practices taking place at the regional level, there are some situations in which local policy decisions may be taken to strengthen these practices. One of these situations concerns peri-urban areas, where the ability of agriculture to provide ecosystem services is highly appreciated (Zasada, 2011). If evaluation studies show that people who score high for an attitudinal indicator expressing a positive relationship between agriculture and the environment are also willing to pay more for agri-environmental practices, and the share of people in the target area of the study giving high scores is large, local policymakers should support those practices with a local subsidy. That support would increase the benefits to society as well as the probability of the local policymakers not losing popularity as a result of applying these measures.

In our study, 25% of the respondents scored 5 for the carbon sequestration statement, and, if we also consider the respondents who scored 4, the percentage increases to more than 60%. Conversely, only 5% of the respondents scored 1 for that statement. As individuals scoring high for the attitudinal statement are those who are willing to pay more, the decision to introduce a local tax to support the adoption of agri-environmental practices further in the peri-urban area of Milan would benefit the largest part of the population in Milan.

Another policy implication of our results may be to exploit the differing willingness to pay for agro-environmental practices in peri-urban areas through the introduction of a financial system involving donations. The donation system would allow the exploitation of the higher WTP of individuals who think that a strong positive link exists between agriculture and the environment, while avoiding the disappointment of people who do not see this link. Of course, an information campaign should be organised to show clearly how the money collected through donations will be used, which agri-environmental practices will be supported and what the ecological benefits of a greater uptake of those practices will be for the citizens. To show the effectiveness of the donations, the municipality or a related association could produce a yearly report on how the money from the donations has been used and how much the environment-friendly agricultural practices targeted by donations in the peri-urban area have increased.

One may argue that the CE of our study included a compulsory taxation and thus the results are based on a system in which the individuals are forced to pay at least something to move away from the status quo. To account for this, we may think of a mixed system that combines a minimum additional tax to support the agri-environmental practices and a voluntary additional donation that would keep the higher WTP of individuals who score higher for the attitudinal statement.

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Incorporating attitudes into the evaluation of preferences regarding agri-environmental practices

Petr Mariel and Linda Arata

On-Line Appendix.

Appendix A

TABLE A1 Estimation of the three-class LC model with an indicator

	Estimate	p-value	
Parameters of the utility equation			
Class 1			
ASC1	2.20	0.12	
ASC2	1.58	0.24	
Tax	-0.33	<0.00	***
Organic medium	-0.10	0.91	
Organic high	-0.35	0.64	
Forest medium	1.64	0.01	***
Forest high	2.98	<0.00	***
Strips medium	1.67	0.03	**
Strips high	-0.16	0.84	
Cover crops	-0.07	0.92	
Class 2			
ASC1	3.51	<0.00	***
ASC2	3.39	<0.00	***
Tax	-0.02	<0.00	***
Organic medium	0.40	<0.00	***
Organic high	1.06	<0.00	***

Forest medium	0.55	<0.00	***
Forest high	0.93	<0.00	***
Strips medium	0.55	<0.00	***
Strips high	0.94	<0.00	***
Cover crops	0.46	<0.00	***
Class 3			
ASC1	0.90	<0.00	***
ASC2	1.21	<0.00	***
Tax	-0.03	<0.00	***
Organic medium	0.27	0.01	**
Organic high	0.17	0.14	
Forest medium	0.14	0.21	
Forest high	0.07	0.55	
Strips medium	0.08	0.47	
Strips high	0.14	0.22	
Cover crops	0.25	<0.00	***
Parameters of the class 2 allocation equation			
Constant	-2.52	<0.00	***
Age	-0.01	<0.00	***
Degree	-0.84	<0.00	***
Employed	0.12	0.43	
Family size	0.02	0.81	
Middle-income class	0.07	0.68	
High-income class	0.38	0.07	*
Male	-0.19	0.14	
Carbon sequestration	1.26	<0.00	***
Residuals from auxiliary regression	-1.21	<0.00	***
Parameters of the class 3 allocation equation			
Constant	2.54	<0.00	***
Age	-0.01	0.03	**
Degree	-0.71	<0.00	***
Employed	0.45	<0.00	***
Family size	-0.07	0.31	
Middle-income class	0.00	0.99	
High-income class	-0.36	0.09	*
Male	0.22	0.10	*
Carbon sequestration	-0.16	0.22	
Residuals from auxiliary regression	-0.08	0.59	

Log-lik.	-2749.30
N	3294.00
K	50.00
AIC	5598.60
BIC	5903.59

CAIC	5953.59

*,**, *** indicate 10%, 5%, 1% significance level respectively

TABLE A2 Estimation of the four-class LC model with an indicator

	Estimate	p-value	
Parameters of the utility equation			
Class 1			
ASC1	1.94	0.05	**
ASC2	1.42	0.14	
Tax	-0.31	<0.00	***
Organic medium	-0.02	0.98	
Organic high	-0.36	0.58	
Forest medium	1.54	0.01	***
Forest high	2.87	<0.00	***
Strips medium	1.69	0.02	**
Strips high	-0.10	0.87	
Cover crops	0.10	0.88	
Class 2			
ASC1	0.42	0.04	**
ASC2	0.86	<0.00	***
Tax	-0.01	0.12	
Organic medium	-0.07	0.59	
Organic high	-0.17	0.22	
Forest medium	0.06	0.66	
Forest high	-0.12	0.41	
Strips medium	-0.18	0.20	
Strips high	-0.11	0.40	
Cover crops	0.08	0.44	
Class 3			
ASC1	1.78	<0.00	***
ASC2	1.91	<0.00	***
Tax	-0.11	<0.00	***
Organic medium	1.30	<0.00	***
Organic high	1.25	<0.00	***
Forest medium	0.35	0.14	
Forest high	0.72	0.01	***
Strips medium	1.11	<0.00	***
Strips high	1.76	<0.00	***
Cover crops	1.07	<0.00	***
Class 4			
ASC1	11.16	0.80	
ASC2	11.07	0.80	
Tax	-0.01	<0.00	***
Organic medium	0.45	<0.00	***
Organic high	1.17	<0.00	***
Forest medium	0.55	<0.00	***
Forest high	0.87	<0.00	***
Strips medium	0.48	<0.00	***

Strips high	0.98	<0.00	***
Cover crops	0.40	<0.00	***
Parameters of the class 2 allocation equation			
Constant	1.49	<0.00	***
Age	-0.01	0.01	***
Degree	-0.61	<0.00	***
Employed	0.36	0.02	**
Family size	0.14	0.04	**
Middle-income class	0.12	0.46	
High-income class	-0.27	0.25	
Male	0.74	<0.00	***
Carbon sequestration	-0.27	0.04	**
Residuals from auxiliary regression	0.09	0.53	
Parameters of the class 3 allocation equation			
Constant	0.88	0.10	*
Age	-0.01	0.04	**
Degree	-0.83	<0.00	***
Employed	0.24	0.14	
Family size	-0.29	<0.00	***
Middle-income class	0.18	0.29	
High-income class	0.10	0.67	
Male	-0.47	<0.00	***
Carbon sequestration	0.42	<0.00	***
Residuals from auxiliary regression	-0.64	<0.00	***
Parameters of the class 4 allocation equation			
Constant	-2.77	<0.00	***
Age	-0.01	0.06	*
Degree	-0.89	<0.00	***
Employed	0.17	0.25	
Family size	0.02	0.79	
Middle-income class	-0.04	0.79	
High-income class	0.23	0.28	
Male	-0.25	0.07	*
Carbon sequestration	1.24	<0.00	***
Residuals from auxiliary regression	-1.23	<0.00	***

Log-lik.	-2645.4
N	3294
K	70
AIC	5430.8
BIC	5857.79
CAIC	5927.79

*,**, *** indicate 10%, 5%, 1% significance level respectively

Appendix B

TABLE B.1 Parameter estimates using different indicators as the endogenous variable

	Carbon sequestration			Preserve biodiversity			Water quality			Pollution		
Class 2 allocation equation	Estimate	p-value		Estimate	p-value		Estimate	p-value		Estimate	p-value	
Constant	-2.05	0.00	***	-1.56	0.00	***	-1.45	0.00	***	-0.77	0.01	***
Age	-0.01	0.08	*	0.00	0.51		0.00	0.53		0.01	0.13	
Degree	-0.37	0.00	***	-0.19	0.05	**	-0.15	0.14		-0.24	0.02	**
Employed	-0.10	0.34		0.00	0.97		-0.07	0.49		0.01	0.89	
Family size	0.11	0.02	**	0.11	0.02	**	0.12	0.01	***	0.09	0.06	*
Middle-income class	0.19	0.08	*	0.14	0.18		0.20	0.06	*	0.09	0.43	
High-income class	0.79	0.00	***	0.75	0.00	***	0.83	0.00	***	0.65	0.00	***
Male	0.27	0.00	***	0.48	0.00	***	0.48	0.00	***	0.25	0.01	***
Carbon sequestration	0.80	0.00	***	0.49	0.00	***	0.47	0.00	***	0.46	0.00	***
Residuals from auxiliary regression	-0.70	0.00	***	-0.51	0.00	***	-0.27	0.00	***	-0.42	0.00	***
Log-lik.	-2825.80			-2830.30			-2829.50			-2830.40		
Auxiliary regression												
Constant	3.34	0.00	***	4.05	0.00	***	4.12	0.00	***	2.72	0.00	***
Factor 1	0.49	0.00	***	0.69	0.00	***	0.73	0.00	***	-0.19	0.00	***
Factor 2	0.34	0.00	***	-0.07	0.03	**	-0.02	0.51		0.83	0.00	***
Environmental NGO member	-0.04	0.76		-0.07	0.43		0.07	0.47		0.23	0.10	*
Number of visits for leisure	0.03	0.73		0.01	0.85		-0.03	0.70		0.10	0.32	
Age	0.00	0.11		0.00	0.46		0.00	0.65		-0.01	0.16	
Degree	0.21	0.02	**	0.06	0.37		-0.06	0.36		-0.11	0.28	
Employed	0.04	0.67		-0.13	0.05	*	0.01	0.93		-0.10	0.38	
Family size	-0.02	0.59		0.06	0.06	*	0.00	0.98		0.03	0.47	
Middle-income class	-0.05	0.63		0.06	0.41		-0.09	0.24		0.13	0.25	
High-income class	-0.09	0.49		0.00	0.99		-0.17	0.11		-0.01	0.95	
Male	0.14	0.09	*	-0.20	0.00	***	-0.18	0.01	***	0.01	0.88	
Refutability test		0.488			0.01	***		0.01	***		0.02	**

	Air quality			Soil erosion			Biodiversity loss		
Parameters of the class 2 allocation equation	Estimate	p-value		Estimate	p-value		Estimate	p-value	
Constant	-1.44	0.00	***	-1.66	0.00	***	-0.56	0.05	**
Age	0.00	0.82		-0.01	0.04	**	0.00	0.49	
Degree	-0.16	0.12		-0.17	0.08	*	-0.28	0.00	***
Employed	-0.10	0.38		-0.10	0.38		-0.02	0.89	
Family size	0.13	0.01	***	0.09	0.06	*	0.08	0.10	*
Middle-income class	0.17	0.12		0.06	0.56		0.14	0.19	
High-income class	0.75	0.00	***	0.63	0.00	***	0.61	0.00	***
Male	0.37	0.00	***	0.34	0.00	***	0.24	0.01	***
Carbon sequestration	0.45	0.00	***	0.67	0.00	***	0.40	0.00	***
Residuals from auxiliary regression	-0.29	0.01	***	-0.62	0.00	***	-0.18	0.04	**
Log-lik.	-2830.5			-2823.50			-2829.00		
Auxiliary regression									
Constant	4.04	0.00	***	3.24	0.00	***	2.40	0.00	***
Factor 1	0.67	0.00	***	0.61	0.00	***	-0.03	0.59	
Factor 2	-0.04	0.17		0.12	0.00	***	0.77	0.00	***
Environmental NGO member	-0.11	0.17		0.18	0.06	*	0.20	0.16	
Number of visits for leisure	0.07	0.18		-0.07	0.29		0.12	0.24	
Age	0.00	0.97		0.01	0.00	***	0.00	0.54	
Degree	-0.07	0.22		-0.02	0.80		-0.01	0.93	
Employed	0.14	0.03	**	0.04	0.57		-0.07	0.52	
Family size	-0.03	0.34		0.03	0.41		0.10	0.05	**
Middle-income class	0.00	0.97		0.15	0.06	*	0.05	0.69	
High-income class	0.02	0.79		0.22	0.05	**	0.23	0.17	
Male	0.09	0.10	*	0.14	0.05	**	0.14	0.17	
Refutability test		0.01	***		0.078	*		0.032	**

*,**, *** indicate 10%, 5%, 1% significance level respectively

Table B.2 Estimation of the LCM based on an ordered logit auxiliary regression

		Estimate	p-value	
Parameter of the utility equation				
Class 1				
ASC1		0.29	0.27	
ASC2		0.58	0.02	*
tax		-0.10	0.00	***
organic medium		0.70	0.00	***
organic high		0.48	0.03	*
forest medium		0.49	0.01	*
forest high		0.62	0.00	**
strips medium		0.49	0.01	*
strips high		0.41	0.04	*
cover crops		0.68	0.00	***
Class 2				
ASC1		1.45	0.00	***
ASC2		1.51	0.00	***
tax		-0.02	0.00	***
organic medium		0.30	0.00	***
organic high		0.62	0.00	***
forest medium		0.33	0.00	***
forest high		0.48	0.00	***
strips medium		0.28	0.00	***
strips high		0.55	0.00	***
cover crops		0.33	0.00	***
Parameter of the class 2 allocation equation				
constant		0.83	0.03	*
age		0.00	0.95	
degree		-0.27	0.01	**
occupied		-0.04	0.69	
Family size		0.13	0.00	**
middle income class		0.19	0.08	.
high income class		0.73	0.00	***
male		0.30	0.00	**
carbon sequestration		0.17	0.00	***
residuals from auxiliary regression		-1.53	0.00	***
LogLik	-2833.9	-2828		
N	3294	3294		
K	28	30		
AIC	5722	5716		
BIC	5892.8	5899		
CAIC	5920.8	5929		

*,**, *** indicate 10%, 5%, 1% significance level respectively

TABLE B.3 Estimates of the ordered logit auxiliary regression

	Estimate	*p-value*	
Constant			
Factor 1	1.09	<0.00	***
Factor 2	0.67	<0.00	***
Environmental NGO member	0.01	0.98	
Number of visits for leisure	0.08	0.61	
Age	0.01	0.14	
Degree	0.35	0.04	**
Occupied	0.10	0.61	
Family size	-0.02	0.78	
Middle-income class	-0.11	0.58	
High-income class	-0.17	0.54	
Male	0.30	0.07	*
Threshold 1	-2.98	<0.00	***
Treshold 2	-1.64	<0.00	***
Treshold 3	0.21	0.64	
Treshold 4	2.11	<0.00	***

*,**, *** indicate 10%, 5%, 1% significance level respectively