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ABSTRACT. Specialised literature on the uptake of agri-environmental schemes (AES) has paid little attention to how this can be influenced by the different types of agricultural systems. This paper analyses the heterogeneity of farmers' preferences towards these schemes, distinguishing between different sub-systems within the same agricultural system. We use the choice experiment method to analyse the case study of three olive grove sub-systems in southern Spain, with the sub-systems ranging from extensive to intensive. The results reveal inter and intra sub-system heterogeneity of farmers' preferences towards AES both in general and specifically related to scheme attributes. A variety of factors appear to lie behind inter sub-system heterogeneity, especially those associated with sub-system specificities (principally, the type of joint production). Likewise, numerous factors play a role in intra sub-system heterogeneity, most of them related to farm/farmer socioeconomic and physical characteristics. These findings will help in the design of more efficient AES.

KEYWORDS: Agri-environmental schemes; Olive groves; Ecological focus areas; Preference heterogeneity; Choice experiment.

1. Introduction

Agri-environmental schemes (AES) are the primary tool used by the European Union (EU) to promote the production of public goods by specific agricultural systems. AES consist of voluntary, incentive-based, per-hectare payments aimed at compensating farmers for their environmentally-friendly practices (Espinosa-Goded, Barreiro-Hurlé, and Ruto 2010; Uthes and Matzdorf 2013). They are frequently implemented regionally on a multi-annual basis and are commonly considered to be the most suitable method of promoting the production of public goods (OECD 2001; Hart et al. 2011). To give an idea of their importance, it is worth pointing out that the aggregate expenditure assigned to AES is €27 billion for the 2014-2020 programming period (European Parliament 2015).

Smart AES design requires a targeted focus on producing public goods (targeting) and a suitable adaptation to the production process of these goods by each agricultural system (tailoring) (OECD 2001; Hart et al. 2011). This has been pointed out by previous literature highlighting the inefficiency of most of the AES implemented so far in the EU (Kleijn and Sutherland 2003; Batáry et al. 2015). In recent years, the use of innovative approaches such as result-oriented (Burton and Schwarz 2013) and collective schemes (Franks 2011; Stallman

2011) have been recommended to improve the efficiency of this policy instrument. However, any improvement in terms of targeting and tailoring the schemes requires a more in-depth knowledge of the factors influencing farmers' uptake (OECD 2008; Hart et al. 2011). As shown by a large body of literature, there is a large heterogeneity of farmers' preferences towards AES – and ultimately with respect to uptake – which mainly relates to: i) what public goods are produced in the farm and how (joint production); ii) farm/farmer socioeconomic factors; and iii) extrinsic factors. The first source of heterogeneity includes physical and agronomic factors (location, slope, soil type, etc.) (Hynes and Garvey 2009; Franco and Calatrava-Leyva 2010), physical farm characteristics (farm size, plot configuration, etc.) (Ducos, Dupraz, and Bonnieux 2009; Adams, Pressey, and Stoeckl 2014), farming/cropping system (Espinosa-Goded, Barreiro-Hurlé, and Ruto 2010; Hynes and Garvey 2009), and farm management (use of technology, resource use, etc.) (Wynn, Crabtree, and Potts 2001; Calatrava-Leyva, Franco, and González-Roa 2007). With regards to farm/farmer socioeconomic factors, preference heterogeneity mainly derives from legal features of the farm (ownership, legal status, etc.) (Defrancesco et al. 2008; Ducos, Dupraz, and Bonnieux 2009; Ruto and Garrod 2009), farmer socio-demographic characteristics (age, education level, etc.) (Espinosa-Goded, Barreiro-Hurlé, and Ruto 2010; Grammatikopoulou, Pouta, and Myyrä 2015), and farmer attitudes and knowledge (environmental consciousness, knowledge of the scheme options, etc.) (Ducos, Dupraz, and Bonnieux 2009; Hynes and Garvey 2009; Ruto and Garrod 2009). Finally, among the factors extrinsic to the farm, of particular note are expectations of agricultural markets (Hodge 2007), policy implementation (e.g. competition and integration with other measures) (Uthes and Matzdorf 2013) and social norms (Defrancesco et al. 2008). Most of these factors are interrelated and can be individual and/or region/system specific. Thus, despite the huge effort made by the research community, there is still a pressing need to improve our understanding of heterogeneous AES uptake in different contexts (Siebert, Toogood, and Knierim 2006; Uthes and Matzdorf 2013).

One of the issues deserving further attention from researchers is how the different agricultural systems and their different types of joint production of private and public goods can influence AES uptake. The fact that the production of these goods varies significantly across agricultural systems (Cooper, Hart, and Baldock 2009) suggests that the sources of heterogeneity regarding AES enrolment very likely vary across systems as well. In this regard, studies to date have commonly highlighted the different level of farming intensification as a strong determiner of AES uptake (OECD 2001; Hart et al. 2011), with intensive agricultural systems exhibiting lower uptake compared to extensive ones (Ducos, Dupraz, and Bonnieux 2009; Hynes and Garvey 2009). However, the production levels and processes of public goods not only differ across different agricultural systems, but also within each agricultural system (Cooper, Hart, and Baldock 2009; Hart et al. 2011). Similarly, if farmer resource allocation differs between agricultural sub-systems, it is likely that farmers' preferences towards AES will also be heterogeneous according to the sub-system they operate. This has been implicitly noted before by relating farming intensity with AES enrolment (Wynn, Crabtree, and Potts 2001; Defrancesco et al. 2008). However, to the authors' knowledge, no papers distinguish between sub-systems within the same cropping system when analysing farmers' preference heterogeneity towards AES. The present study aims to add to the knowledge on this issue by testing the hypothesis that farmers' preferences towards AES vary (I) *across* and (II) *within* sub-systems of the same cropping system.

In this paper, we use the choice experiment method to analyse farmers' preferences towards AES, distinguishing between three olive grove sub-systems in southern Spain: mountainous rain-fed, plain rain-fed, and plain irrigated olive groves, representing a range from more extensive to more intensive sub-systems. The main objective of this study is to analyse how farmers' preferences towards AES vary across and within agricultural sub-systems (i.e. inter and intra-sub-system heterogeneity, respectively). Moreover, in the analysis we include some innovative issues that have been the focus of very little research to date, such as the use of ecological focus areas (EFA) and collective participation in AES contracts. The results of this analysis may be very useful for policy-making, since they can be used to support a more efficient design of AES.

The remainder of the paper is structured as follows: The next section describes the methodology, the data gathering and the case study. The main results are presented and discussed in the third section, while the fourth section outlines the main conclusions.

2. Data and methods

2.1. Description of the case study

The case study selected for the analysis is olive growing in Andalusia (southern Spain), given that this is the main crop grown in this region (over 1.5 million hectares, 48% of Andalusian farmland) with a great potential for improvement in the production of environmental public goods (Villanueva et al. 2014). As Villanueva et al. (2015) suggest, the type of olive grove sub-system can influence farmer willingness to participate in AES. We therefore analyse the three main olive grove sub-systems in Andalusia, namely mountainous rain-fed (MOG), plain rain-fed (ROG) and plain irrigated (IOG) olive groves, representing 33%, 32% and 17%, respectively, of the area dedicated to olive groves in the region (CAP 2008). These three sub-systems share some characteristics such as low-to-moderate tree density (with fewer than 150 olive trees/ha), more than one stem per tree, and they are also well-established groves (more than 20 years old). However, they have distinctive characteristics which leads to different resource allocation, from the more extensive (MOG) to the more intensive (IOG) use of inputs (Gómez-Limón and Arriaza 2011). MOG is usually located on steep slopes and poor land. Consequently, it presents low yields and, as a result, low farm incomes and a notable risk of abandonment. ROG is located in flat areas and normally has better and deeper soils, with higher yields and farm income than that of MOG, and therefore is associated with a lower risk of abandonment. IOG is normally “irrigated ROG”. IOG shares roughly the same tree density and soil quality characteristics with ROG but has higher yields as irrigation is also associated with a higher use of agricultural inputs (Villanueva et al. 2014). Correspondingly, IOG typically yields the highest farm income of the three olive grove sub-systems and has the lowest risk of abandonment.

2.2. Data collection and sample description

A multi-stage sampling procedure was employed. In the first stage, 5 out of 52 agricultural districts in Andalusia were randomly selected, with the probability of being selected proportional to olive grove area. The sampled districts cover 453,682 ha and account for 31.0% of Andalusian olive groves. In the next stage, at least 60 personal interviews were conducted per district (randomly selecting 10 towns/villages for each district), giving 327 completed questionnaires. Of those, 34 were protests, reducing the total number of valid interviews to 293, with 75 MOG, 116 ROG and 102 IOG. The interviews were carried out between October 2013 and January 2014.

Table 1 contains descriptions of the farms surveyed according to the three sub-systems under study. The characteristics of the farms surveyed coincide with the description of the sub-systems given above and are consistent with the literature (Gómez-Limón and Arriaza 2011). The different level of intensification of the sub-systems is clearly reflected in the significantly different yearly average yield: low for MOG (2,615 kg/ha), medium for ROG (4,416 kg/ha), and high for IOG (6,337 kg/ha). In addition, there is a significant difference in the slope and –obviously– the use of irrigation water. However, there are no significant differences regarding farm size – i.e. olive grove and total area – or tree density, which are two factors that strongly influence the production of public goods in olive growing, as highlighted in Villanueva et al. (2014). Farm management also differs between the three olive grove sub-systems. For instance, although the use of conventional olive-growing techniques is widespread in all three, these techniques are used to a greater extent in ROG than in MOG or IOG. Most of the remaining farmers use integrated farming techniques, while scarcely any organic farming techniques are used. As regards agri-environmental practices, significant differences are found between MOG and the other two sub-systems. This is evidenced in variables such as the percentage of cover crops area and EFA within olive tree farmland, as well as participation in the current AES implemented in Andalusian olive growing.

Table 1. Description of the olive grove sub-systems (numeric variables show st. dv.).

Type	**Variable**	**MOG** *Mean*	**MOG** *St.dv.*	**ROG** *Mean*	**ROG** *St.dv.*	**IOG** *Mean*	**IOG** *St.dv.*	***p-value***[1]
Farm characteristics	Olive tree area (ha)	23.3	31.2	34.7	64.4	33.9	67.8	0.494
	Total area (ha)	24.1	32.2	48.4	96.0	37.6	69.2	0.368
	Tree density (trees/ha)	122.7	44.7	119.7	57.4	138.0	72.5	0.367
	Slope (%)	21.7 ^{b}	8.8	4.6 ^{a}	3.7	5.2 ^{a}	4.2	0.000
	Family labour over total farm labour [*Famlabour*] (%)	67.2	31.0	63.4	30.9	62.8	29.9	0.506
	Irrigation water (m^3/ha)	0 ^{a}	0	0 ^{a}	0	923 ^{b}	589	0.000
	Yield (kg/ha)	2615 ^{a}	1596	4416 ^{b}	1571	6337 ^{c}	2164	0.000
Farm management	Cover crops / olive tree area (%)	42.6 ^{b}	27.7	17.0 ^{a}	17.8	21.6 ^{a}	18.4	0.000
	EFA / olive tree area (%)	3.2 ^{b}	4.0	0.5 ^{a}	1.1	0.7 ^{a}	1.5	0.000
	Ground harvested / total olive harvested [*Groundharv*] (%)	12.4 ^{a}	19.1	11.8 ^{a}	18.0	23.8 ^{b}	28.5	0.012
	Use of conventional techniques	60.0 ^{a}		76.7 ^{b}		54.9 ^{a}		0.002
	Use of restrictive management to manage cover crops	44.0 ^{b}		19.0 ^{a}		39.2 ^{b}		0.000
	Participation in current AES [*AESparticip*]	29.3 ^{a}		8.6 ^{b}		16.7 ^{ab}		0.001
Farmer characteristics	Age [*Age*] (years)	52.9	12.9	50.3	12.6	48.5	10.0	0.077
	Farmers' working time on the farm (% of total working time)	46.1	40.8	50.5	39.7	56.3	38.5	0.114
	Education level-at least high school [*Educa2*]	34.7 ^{a}		32.8 ^{a}		52.9 ^{b}		0.005
	Farmer not professionally trained [*No-Training*]	63.5 ^{a}		65.5 ^{a}		36.6 ^{b}		0.000
	Farmer asks for advice at least once a month [*Freqadvi*]	36.0 ^{a}		37.2 ^{a}		51.5 ^{a}		0.052
Farmers' knowledge & perceptions	Perception of cover crops as profitable [*PerCCprofit*] (1-Strongly agree/5-Strongly disagree)	3.64 ^{a}	1.41	3.16 ^{a}	1.47	3.61 ^{a}	1.44	0.025
	Perception of EFA as environmentally beneficial [*PerEFAbenef*] (1-Strongly agree/5-Strongly	4.03 ^{b}	1.30	3.65 ^{a}	1.29	3.84 ^{ab}	1.21	0.048
	Farmer is aware of the AES (at least one) implemented in the region	37.3		25.9		35.3		0.174
	Farmer knows the cover crops requisite within cross-compliance [*KnowCC*]	78.4		73.9		84.7		0.161
	Farmer perception that there will be no farm takeover [*No-Takeover*]	37.3		42.0		40.6		0.816

[1] Kruskal-Wallis and Chi-square tests were used to examine differences for numeric and categorical variables, respectively. In the case of the latter, Z-test was used to obtain the ranking. Superscripts ^{a}, ^{b}, and ^{c} indicate the differences between the three sub-systems for each variable; sharing the same letter implies no significant statistical differences at the 5% level.

Source: Own elaboration.

Regarding farmers' characteristics, no significant differences were found for age or for time dedicated to farm work. However, IOG farmers show a higher level of education and professional training. There are also differences between the sub-systems in terms of farmer perception, with MOG and IOG farmers viewing the use of cover crops and EFA in a more positive light than ROG farmers do. In all three sub-systems, farmers show a higher level of knowledge about other policy tools, such as cross-compliance, than they do about AES.

2.3. Choice experiment: Attributes and experimental design

The choice experiment method is a stated preference valuation technique (for an extensive explanation of the method, see Hensher et al. 2005) well suited to measuring the marginal value of the attributes of a good or policy instrument (Ruto and Garrod 2009). The underlying assumption is that a farmer's choice of voluntary policy schemes depends on the specific characteristics or attributes of these schemes (Christensen et al. 2011). The use of this approach to support policy-making has sharply increased in the last six years, especially regarding AES design (Ruto and Garrod 2009; Espinosa-Goded, Barreiro-Hurlé, and Ruto 2010; Christensen et al. 2011). The above studies support the use of choice experiments as the chosen approach for this empirical study.

As in any other application of choice experiments, attributes and levels of the good or policy under study are established. Here, six attributes were used to build possible AES, three of them linked to agricultural management (of those three, two are related to soil management and one to EFA), two are related to policy design and the last to the payment (see Table 2). The first three are practices aimed at improving farmers' provision of environmental public goods (especially carbon sequestration, biodiversity, soil conservation, and landscape aesthetics) (Stoate et al. 2009; EC 2011; Villanueva et al. 2014).

Of the agricultural attributes, the two related to soil management focus on the use of cover crops. The use of cover crops very likely represents the most useful agricultural practice in olive growing in terms of enhancing the production of environmental public goods (Villanueva et al. 2014). The level of production of these public goods derived from the use of cover crops in this agricultural system depends on the area covered and how farmers manage it (Barranco, Fernández-Escobar, and Rallo 2008). Thus, the area covered by cover crops and its management are the two related attributes included in the choice experiments. For the attribute *Cover crops area* (CCAR), two levels were included: 25% and 50% of the olive grove area (CCAR-25% and CCAR-50%, respectively) (see Table 2). These levels were set based on a literature review – especially Gómez-Limón and Arriaza (2011) – and expert knowledge. As regards to the attribute *Cover crops management* (CCMA), two levels were considered: free (CCMA-Free) and restrictive management (CCMA-Restr). The latter corresponds to the management established in the current AES that is specifically dedicated to olive growing (*Sub-measure 7* or SM7), which basically restricts the use of both tillage and herbicide in cover crops management, while the former implies no restrictions other than those that are part of cross-compliance.

The attribute *Ecological focus areas* (EFA) was included in the choice experiment to pre-emptively explore a hypothetical future implementation of the EFA requisite of the Common Agricultural Policy (CAP) 'green payment' in permanent crops such as olive groves[1]. Our aim is to analyse farmers' preferences towards EFA, given the few studies to date that have provided information on this subject (of those that do, it is worth highlighting Schulz, Breustedt, and Latacz-Lohmann 2014; and Villanueva et al. 2015). Levels were set at 0 and 2% of the olive grove plots covered by EFA (EFA-0% and EFA-2%, respectively). The first level is equivalent to the current eligibility requirements for the 'green payment' in permanent crops. The second is below the 5% of EFA established for arable land in CAP regulations, and was decided upon after taking into account both the current lack of these kind of areas in Andalusian olive groves and the difficulties of increasing the share of EFA in permanent crops (Gómez-Limón and Arriaza 2011).

Table 2. Attributes and levels used in the choice set design[1].

Attribute [Acronym]	Explanation	Levels
Cover crops area [CCAR]	Percentage of the olive grove area covered by cover crops	25% and 50%
Cover crops management [CCMA]	Farmer's management of the cover crops	Free and restrictive management
Ecological focus areas [EFA]	Percentage of the olive grove plots covered by ecological focus areas	0% and 2%
Collective participation [COLLE]	Participation of a group of farmers (at least 5) with farms located in the same municipality	Individual and collective participation
Monitoring [MONI]	Percentage of farms monitored each year	5% and 20%
Payment [PAYM]	Yearly payment per ha for a 5-year AES contract	€100, 200, 300 and 400/ha per year

[1] The status quo alternative represents non-participation, which means that the attributes remain at the current levels for each farmer.

Source: Own elaboration.

[1] Unlike arable crops for which a minimum of 5% of farmland must be devoted to EFA to receive the 'green payment', permanent crops are eligible for green payment without any minimum EFA requisite (see Regulation EC 1307/2013, Art. 43-47). Therefore, this research aims to explore olive growers' behaviour regarding the implementation of EFA in their farmland by means of considering the inclusion of this requisite in AES.

Collective participation and monitoring levels are the two design attributes included in the choice experiments. Collective contracts represent a promising way of reducing transaction costs (mainly public) while increasing the environmental effectiveness of policy instruments (Uthes and Matzdorf 2013). Although collective participation in AES has attracted growing attention in academia (see Franks 2011; and Stallman 2011, among others), estimates of the compensation needed to incentivise collective rather than individual participation are almost lacking (of the few relevant works in this respect, worthy of mention are those of Kuhfuss et al. 2015; and Villanueva et al. 2015). For this reason, we included the attribute *Collective participation* (COLLE) – with two levels, collective and individual participation – in the analysis. For participation to be considered collective, a group of at least five farmers whose farms are located in the same municipality have to sign the same AES contract. With regards to *Monitoring* (MONI), since previous literature shows that the level of monitoring influences farmers' preferences towards AES (e.g. Broch and Vedel 2012), we decided to include this attribute in order to identify potential relationships with the other attributes. The two levels set for MONI are 5 and 20% of olive grove farms monitored (MONI-5% and MONI-20%, respectively). The lower level was set as equal to the normal monitoring level of CAP measures, while the higher level was chosen to make a clear difference to the farmers.

Finally, with regard to the *payment* attribute (PAYM), four levels were established according to payments in SM7 (€204-286/ha per year). Two levels (€200/ha and €300/ha) were set in line with these payments, while two further levels (€100/ha and €400/ha) were set as minimum and maximum payments.

With regards to the experimental design, a fractional factorial design and optimal orthogonal in the differences proposed by Street and Burgess (2007) was used to create a more manageable number of options, reducing the possible combinations (1924) to 192 profiles[2] (D-efficiency=91.3%). The 192 choice sets were divided into 24 blocks, each with 8 choice sets, with one farmer responding to one block[3]. In each choice set, farmers were asked to choose between two alternatives, in addition to a possible no-choice (i.e. status quo (SQ) representing the "business as usual" option). As each farmer's status quo may be different, several questions were included in the questionnaire to characterise farmers' individual current conditions (specifically for the attributes CCAR, CCMA, and EFA).

[2] This design allowed for an analysis of main and second-order effects. Second-order effects were analysed but found to be non-significant. Therefore, the analysis focuses on main effects only.

[3] The experimental design was carried out so as to keep balanced combinations of choice sets within each block, so a great effect from a low number of repetitions of each block is not expected.

2.4. *Model specification: Error Component Random Parameter Logit (EC_RPL)*

Random parameter logit models (RPL) with an additional error component were used to analyse the choices between alternative AES. The RPL model is well suited to analysing preference heterogeneity since it allows for random taste variation, unrestricted substitution patterns and correlation in unobserved factors (Train 2003; Hensher et al. 2005). The error component RPL model (EC_RPL) outperforms the classic RPL specification by including an additional error component in the utility function capturing the error variance common to both alternatives A and B (i.e. it accounts for the fact that respondents may treat the hypothetical AES-alternatives [A, B] differently to the status quo) (Scarpa, Campbell, and Hutchinson 2007). The EC_RPL model has been used before in this type of analysis (Espinosa-Goded, Barreiro-Hurlé, and Ruto 2010; Broch and Vedel 2012), confirming its suitability for this purpose.

In the EC_RPL, the utility function associated with each alternative is expressed as follows:

$$U_{Alt\ A} = \beta'\chi + \beta_S'\chi + \vartheta + \varepsilon \qquad [1]$$

$$U_{Alt\ B} = \beta'\chi + \beta_S'\chi + \vartheta + \varepsilon \qquad [2]$$

$$U_{SQ} = ASC_{SQ} + \beta'\chi + \beta_S'\chi + \gamma S + \varepsilon \qquad [3]$$

where ASC_{SQ} is the alternative-specific constant for the SQ choice, χ is a vector representing the attributes, ϑ is the additional error component (distributed with $N(0,\sigma^2)$), and ε is the random error term, which is assumed to be identically and independently distributed (*iid*) and related to the choice probability with a Gumbel distributed error term. The vector of coefficients (β) reflects individual preferences which, given that these are allowed to vary across individuals, is randomly distributed in the population following a density function $f(\beta_n \mid \theta)$, where θ represents the distribution parameters. β_S represents heterogeneity that can be explained by individual (farm and/or farmer) characteristics. γS captures heterogeneity in preferences for the status quo option explained by a set of individual characteristics (with S representing the vector of characteristics and γ the parameters to be estimated). Choices are modelled following a panel structure, thus with the integer probability involving a product of logit formulae. The joint probability of respondent n choosing alternative i in each of the T choice situations is given by:

$$P[t(n)] = \int_\beta \int_\eta \prod_{t=1}^{T} \frac{\exp\,(\lambda(\beta_n'\chi_{ti}+\vartheta))}{\sum_{j\subset A_t}(\lambda(\beta_n'\chi_{ti}+\vartheta))} f(\beta_n|\theta)\,\varphi(0,\sigma^2)\,d\beta\, d\vartheta \qquad [4]$$

where A_t=(*Alt A, Alt B, SQ*) is the choice set, λ is a scale parameter, $f(\beta_n \mid \theta)$ is the density of the attributes random parameters, and $\varphi(\cdot)$ is the normal density of the error component (ϑ) which equals zero when j=SQ. This integral does not have a closed form so is approximated using simulation methods (Train 2003). Here, models were estimated using 200 Halton draws.

All attributes were assumed to follow a normal distribution, except for PAYM and MONI which are assumed to be non-random.

Two types of EC_RPL models were used in the analysis. First, EC_RPL without interactions were built to compare welfare estimates of farmers from the three sub-systems. Second, EC_RPL with interactions were used to capture heterogeneity in farmers' preferences, both specifically related to each attribute of the choice experiment and generally related to AES enrolment. Interactions of the attributes and the alternate specific-constant (ASC_{SQ}) with farm/farmer characteristics were used to account for, respectively, sources of observed heterogeneity specifically related to the attributes and AES uptake in general. The selection of the final models with interactions was made taking into account the criteria of significance and substantiality (of parameters) and parsimony. In a first step, significant interactions were explored for each sub-system using EC_RPL with a single interaction of one attribute with one variable. In a second step, multiple-interaction models were explored using different combinations of the interactions that had proved significant in the first step, with a particular focus on the significant non-monetary attributes. The four-interaction configuration proved to be the best option in terms of best overall fit and parsimony. The final step consisted of adding interactions with the ASC_{SQ} to the four-interaction models. Due to the parsimony of the models and the potential appearance of problems of multicollinearity, we decided to add two interactions of this type. After having estimated the first six-interaction model – specifically for the IOG sub-system – we decided to seek a similar configuration (i.e. four interactions with the attributes and two with the ASC_{SQ}) for the other two models to facilitate the comparison between the three sub-systems. Table 3 contains a summary of the interactions used in these three main *multiple-interaction models*.

Finally, to explore which interactions hold among the sub-systems, the combinations used for the main multiple-interaction models were replicated for the other sub-systems, thus obtaining the *crossed multiple-interaction models* (shown in Appendix A).

Table 3. Interacting variables with the choice experiment attributes and the ASC_{SQ} in the main multiple-interaction models.

Variable [*Acronym*]	**Units**	**Interacting attribute or constant**	**Olive grove sub-system**
Currently participating in AES in olive groves [*AESparticip*]	[0,1]	CCAR	MOG
Farmer knows the cover crops requisite within cross-compliance [*KnowCC*]	[0,1]	CCAR	ROG
Percentage of olives harvested from the ground [*Groundharv*]	[%]	CCAR	IOG
Perception of cover crops as profitable [*PerCCprofit*]	Likert [1,5][1]	CCMA	MOG
			ROG
Education level-at least high school [*Educa2*]	[0,1]	CCMA	IOG
Perception of EFA as environmentally beneficial [*PerEFAbenef*]	Likert [1,5][1]	EFA	MOG
Farmer not professionally trained [*No-Training*]	[0,1]	EFA	IOG
		ASC_{SQ}	ROG
Olive tree area above 10 ha [*Oliarea10*]	[0,1]	EFA	ROG
Olive tree area above 20 ha [*Oliarea20*]	[0,1]	COLLE	MOG
		ASC_{SQ}	IOG
Farmer's perception that there will be no farm takeover [*No-Takeover*]	[0,1]	COLLE	IOG
Age [*Age*]	[Years]	ASC_{SQ}	MOG
Age above 60 years [*Age60*]	[0,1]	COLLE	ROG
Farmer asks for advice at least once a month [*Freqadvi*]	[0,1]	ASC_{SQ}	MOG
Percentage of family labour over total farm labour [*Famlabour*]	[%]	ASC_{SQ}	ROG
Single payment above €750/ha [*SPaym750*]	[0,1]	ASC_{SQ}	IOG

[1] Likert scale (1-Strongly disagree, 2-Disagree, 3-Neither, 4-Agree, 5-Strongly agree) used for answering the questions: "*Do you agree with the statement 'The use of cover crops will be profitable for my farm in the long term'?*" for *PerCCprofit*; and "*Do you agree with the statement 'Devoting some farmland to EFA provides important environmental benefits'?*" for *PerEFAbenef.*

Source: Own elaboration.

2.5. Welfare analysis and AES scenarios

Marginal rates of substitution between non-monetary and monetary attributes were estimated by calculating the ratio of the coefficient of the former to the negative of the coefficient of the latter [$WTA_{NM} = -(\beta_{NM} / \beta_M)$] (Hensher et al. 2005). These are also called the "implicit prices", representing the willingness to accept (WTA) for a 1% or 1-unit increase in the quantitative attributes (e.g. EFA), or for a discrete change in the qualitative attributes (e.g. from free to restrictive CCMA). We apply the parametric bootstrapping approach by Krinsky and Robb (1986), commonly used in choice experiment applications, to empirically determine the attributes' WTA distributions. The EC_RPL models without interactions were used to compare WTA estimates between sub-systems. These models were chosen instead of EC_RPL with interactions in order to avoid potential unintended effects on welfare estimates resulting from the inclusion of different combinations of interactions.

Total WTA were calculated for the most stringent AES scenarios (i.e. CCAR-50%, EFA-2%, CCMA-Restr, MONI-20%) both for individual and collective participation following the compensating surplus (CS) formula [$CS=-1/\beta_M \times (U_0-U_1)$] proposed by Hanemann (1984).

To test the differences between the WTA and total WTA estimates, the Complete Combinatorial test proposed by Poe, Giraud, and Loomis (2005) was used. It is worth recalling here that we are comparing WTA estimates, so there is no confounding effect due to different scale parameters of the models as these parameters cancel out in the calculations (Scarpa, Thiene, and Train 2008). Nevertheless, we tested the differences between scale parameters using Biogeme 2.0 (Bierlaire 2009) to provide more detailed information on the models.

3. Results and discussion

3.1. Preference heterogeneity across sub-systems

The results of the EC_RPL models for the three sub-systems considering only the attributes and the constant – models with the subscript 'no-i', i.e. without interactions – are presented in Table 4. The three models are highly significant and fit well, with pseudo-R^2 above 0.42. As can be seen in this table, all but one of the attributes are highly significant determinants of choice; all the coefficients show a high statistical significance level (with the exception of MONI and the ASC_{SQ}, which are not significant or, at best, are significant at the 5% level for $ROG_{no\text{-}i}$) and have the expected sign – negative for all of them except PAYM – reflecting farmer disutility, or utility in the case of PAYM. MONI is the attribute that received the least attention from farmers, indicating that the level of monitoring played only a minor role in their choices. All standard deviations of the random parameters were significant indicating that preferences varied significantly within each sub-sample.

The differences across sub-systems can be better observed in Table 5, which shows the resulting mean WTA using the models shown in Table 4. As can be observed in Table 5, three out of the five non-monetary attributes show statistically significant differences in WTA between the three sub-systems. These results provide strong confirmation of Hypothesis I, i.e. farmers' preferences towards AES vary across sub-systems of the same cropping system. Separate results for each attribute are commented on below and discussed in more detail, followed by a note on scheme scenarios.

Table 4. EC_RPL models for the three olive grove sub-systems.

	$\mathbf{MOG_{no\text{-}i}}$		$\mathbf{ROG_{no\text{-}i}}$		$\mathbf{IOG_{no\text{-}i}}$	
	Coef.	*S.e.*	*Coef.*	*S.e.*	*Coef.*	*S.e.*
Attributes & constant						
CCAR-Cover crops area (1% of CCAR)	-0.126 ***	0.017	-0.082 ***	0.014	-0.103 ***	0.015
CCMA-Cover crops management (CCMA-Restr=1)	-1.626 ***	0.433	-4.357 ***	0.489	-1.344 ***	0.300
EFA-Ecological focus areas (1% of EFA)	-0.574 ***	0.132	-0.801 ***	0.132	-0.978 ***	0.168
COLLE-Collective participation (Collective participation=1)	-2.206 ***	0.550	-2.535 ***	0.408	-1.556 ***	0.331
MONI-Level of monitoring (1% of farms monitored)	0.014	0.016	-0.033 *	0.016	-0.008	0.012
PAYM-Payment	0.014 ***	0.002	0.013 ***	0.001	0.013 ***	0.001
ASC_{SQ}	0.272	0.684	-1.179 *	0.530	-1.014	0.577
St.dv. of the parameters						
CCAR	0.104 ***	0.024	0.103 ***	0.014	0.132 ***	0.019
CCMA	3.018 ***	0.577	4.279 ***	0.729	1.903 ***	0.309
EFA	1.384 ***	0.221	0.676 **	0.226	1.145 ***	0.177
COLLE	2.645 ***	0.531	4.437 ***	0.549	1.898 ***	0.333
Error component	3.168 ***	0.477	3.256 ***	0.379	3.262 ***	0.404
Goodness-of-fit						
LL	-377.8		-554.8		-512.6	
AIC	1.298		1.222		1.286	
BIC	1.386		1.284		1.355	
McFadden Pseudo-R^2	0.427		0.456		0.428	
Observations	75		116		102	

*, **, and *** denote significance at the 5, 1, and 0.1% levels, respectively. Significant differences between scale parameters of the sub-systems were tested using Biogeme 2.0 (Bierlaire 2009). The results showed no significant differences when the scale parameters of MOG and IOG were fixed, while significant differences at the 90% level were found when ROG were fixed (both compared to MOG and IOG).

Source: Own elaboration.

For the attribute *cover crops area* (CCAR), there are no significant differences between the three sub-systems, with the mean WTA ranging from €6.5/ha for a 1% increase in cover crops area in ROG to €8.8/ha in MOG. The average status quo level of cover crops area is 43%, 17%, and 22% for MOG, ROG and IOG. These results therefore indicate that the effort made by a MOG farmer to achieve a 1% increase in his/her cover crops area beyond 43% is similar to the effort made by ROG and IOG farmers to do so beyond 17% and 22% of cover crops area, respectively. As a result of the different status quo, MOG farmers would be willing to comply with the level of 50% of cover crops area for a lower compensation (€142/ha on average) than ROG and IOG farmers (€215/ha and €222/ha, respectively)[4]. For the 25% level of cover crops area, the estimates would be €35/ha, €79/ha, and €74/ha, respectively. These results reflect the different intervals for which the use of cover crops – in terms of area – is complementary to the production of private goods; the interval is longer for MOG than for ROG or IOG. For the latter two sub-systems, the fact that the majority of their farmers use cover crops suggests that joint production is complementary at low levels of cover crops area, but becomes competitive at a point lying somewhere between the initial situation (i.e. cover crops area of 17-22%) and 50%, though likely closer to the former level. This is consistent with the idea underscored by specialised literature, namely that extensive agricultural systems exhibit complementary joint production to a greater extent than intensive ones (OECD 2001; Cooper, Hart, and Baldock 2009). However, ROG and IOG show similar WTA, which is not consistent with their different levels of intensification. One possible explanation for this unexpected outcome may be that the higher opportunity costs borne by IOG are countered by the agronomic problems (namely, scarcity of soil water) that ROG faces in order to maintain an extensive area of cover crops.

With regards to *cover crops management* (CCMA), results show a moderately high WTA for this attribute, although significantly higher in ROG – €341.3/ha – compared to the other two sub-systems – €112.4/ha for MOG and €101.1/ha for IOG. The WTA estimates for the three sub-systems reflect the very negative perception farmers have of managing cover crops without tillage and with a restrictive use of herbicides, consistent with farmers' strong preferences for flexibility reported by Espinosa-Goded, Barreiro-Hurlé, and Ruto (2010) and Christensen et al. (2011). The preference for flexibility is more evident for ROG farmers, as they show different patterns of joint production. These farmers perceive a larger trade-off between private and public goods associated with the use of restrictive cover crops management. This is explained by the fact that soil water strongly determines yields, coupled with farmer beliefs that tillage helps to reduce soil water evaporation during the summer season. As a result, most ROG farmers rejected such restrictive management. This, then, is an example of how specific features of joint production can be a source of preference heterogeneity across sub-systems.

Significant differences across sub-systems are also found regarding *ecological focus areas* (EFA), with MOG having a lower WTA – €39.2/ha per additional 1% of the farmland devoted to EFA – compared to ROG and IOG – €63.2/ha and €72.4/ha per additional 1% devoted to these areas, respectively. The initial agricultural condition of the sub-system is reflected in the different intensity of farmers' preferences. Hence, in more intensive olive grove sub-systems (ROG and IOG), where most of the existing EFA have been removed, the

[4] These estimates are produced by calculating the total WTA using Hanemann's proposal (see section 2.5) applied to the change from status quo level CCAR to CCAR-50%, and assuming linearity and zero welfare change for those farmers whose status quo is above that level. The same is done for CCAR-25%.

EFA requisite is perceived as much more stringent than in the more extensive sub-systems (MOG), where fewer such areas have been eliminated. Schulz, Breustedt, and Latacz-Lohmann (2014) also find higher WTA for more intensive agricultural systems, emphasising the higher opportunity costs borne by these systems. Coupled with this, the more visible soil conservation benefits associated with the use of EFA for steep slopes presumably also plays a role in the differences.

Table 5. Mean willingness to accept (WTA) of the attributes (€/ha)[1].

Attributes	MOG	ROG	IOG
CCAR-Cover crops area	8.8 ***,a	6.5 ***,a	7.7 ***,a
CCMA-Cover crops management	112.4 ***,a	341.3 ***,b	101.1 ***,a
EFA-Ecological focus areas	39.2 ***,a	63.2 ***,b	72.4 ***,b
COLLE-Collective participation	153.6 ***,ab	197.5 ***,b	117.2 ***,a
MONI-Level of monitoring	-0.9 a	2.6 *,a	0.7 a

[1] For CCAR, EFA, and MONI, this is € per additional 1% of the olive grove area covered by cover crops, per additional 1% of the olive grove area devoted to EFA, and 1% increase in farms monitored, respectively.

*, **, and *** denote that WTA estimates are significantly different from zero at the 5%, 1%, and 0.1% levels, respectively. The superscripts (a and b) reflect the results of Poe, Giraud, and Loomis (2005) test; sharing superscripts means no significant differences at the 5% level.

Source: Own elaboration.

With regards to *collective participation* (COLLE), there is a significantly higher WTA in ROG (€197.5/ha) compared to IOG (€117.2/ha), with MOG (€153.6/ha) lying between the other two sub-systems. It appears that the greater stringency of the proposed schemes as perceived by ROG farmers also drives up WTA for collective participation. Since ROG farmers doubt their own ability to comply with the requirements proposed, this is echoed in their lack of trust in others' compliance. In the case of MOG and IOG, welfare estimates obtained for collective participation merit further explanation. Since MOG is the more extensive sub-system, one might expect lower WTA for collective participation than in IOG. Two reasons appear to be behind this unexpected result. First, unlike IOG, MOG farms are located in areas with heterogeneous topography, which does not facilitate the mutual monitoring among the members of the collective, thus representing a barrier to building-up the collective (Franks 2011). Second, IOG farmers typically belong to other agricultural collectives such as irrigation districts, and this seems to encourage AES uptake (Espinosa-Goded, Barreiro-Hurlé, and Ruto 2010).

With regards to the *level of monitoring* (MONI), ROG is the only sub-system where this attribute seems to play a role in the choices made by farmers. We interpret it in the same way as we did for collective participation: since ROG farmers perceive a higher level of stringency of the proposed schemes, it would be more difficult for them to comply with these schemes and consequently they would have a greater fear of heightened levels of monitoring.

In terms of an overall comparison of the sub-systems, Table 6 shows estimates of total WTA for the most stringent *AES scenario* with individual and collective participation. Consistent with the previous results, this table shows significant differences across the three sub-system. Results indicate that MOG farmers would participate in these schemes – individually and collectively – in return for a statistically significantly lower payment than IOG and ROG farmers, with the latter showing the significantly highest payments for doing so. These results are in line with the general idea of higher (lower) AES uptake by extensive (intensive) agricultural systems highlighted by the literature (Wynn, Crabtree, and Potts 2001; Defrancesco et al. 2008; Ducos, Dupraz, and Bonnieux 2009; Hynes and Garvey 2009). This is particularly pertinent to the most extensive sub-system (MOG) as opposed to the other two sub-systems. However, the fact that the moderately-intensive sub-system (ROG) shows lower willingness to participate in AES than the more intensive IOG indicates that there may be more factors behind inter sub-system heterogeneity of preferences than simply the level of intensification. One particular such factor may be the different joint production, as discussed above for agri-environmental attributes. Unfortunately, we cannot isolate the extent to which each factor is responsible for this heterogeneity.

Table 6. Total willingness to accept (WTA) for the most stringent AES scenarios (€/ha)[1].

Attributes	**MOG**	**ROG**	**IOG**
Individual most stringent AES	215.0^{***,a}	645.5^{***,c}	409.4^{***,b}
Collective most stringent AES	368.9^{***,a}	843.0^{***,c}	526.6^{***,b}

[1] These AES share the requisites CCAR-50%, CCMA-Restr, EFA-2%, and MONI-20%, but differ in the type of participation (i.e. individual and collective). *** denotes that total WTA estimates are significantly different from zero at the 0.1% level. The superscripts (^{a}, ^{b}, and ^{c}) denote the results of Poe, Giraud, and Loomis (2005) test; sharing superscripts means no significant differences at the 5% level.

Source: Own elaboration.

3.2. Preference heterogeneity within sub-systems

Table 7 shows the main *multiple-interaction models* – the subscript 'i' means that the model includes interactions – exploring the heterogeneity related to farm/farmer characteristics for the three olive grove sub-systems. Like the models above, these models are highly significant – with the exception of MONI, all the attributes are highly significant and have the expected sign – and the overall fit is very good (pseudo-R^2 over 0.44). These models confirm Hypothesis II, i.e. farmers' preferences towards AES vary within sub-systems of the same cropping system. The intra sub-system high heterogeneity of preferences is reflected in the fact that all standard deviations of the random parameters, the interaction parameters, and covariates interacting with ASC_{SQ} are significant. These models show that there is a wide variety of factors that influence farmers' preferences towards AES within the same sub-system, including variables related to the three abovementioned sources of heterogeneity: i) sub-system joint production, namely physical farm characteristics and farm management; ii) farm/farmer socioeconomic factors, namely farm/farmer socioeconomic characteristics and farmer knowledge and perceptions; and iii) extrinsic factors, particularly the implementation of other policy measures. Most of these factors have been reported in earlier studies of agricultural systems and/or regions (Wynn, Crabtree, and Potts 2001; Siebert, Toogood, and Knierim 2006; Hynes and Garvey 2009; Ruto and Garrod 2009; Espinosa-Goded, Barreiro-Hurlé, and Ruto 2010; Franco and Calatrava-Leyva 2010; Rodríguez-Entrena and Arriaza 2013) but, to the authors' knowledge, this is the first study to reveal the influence of these factors at a sub-system level.

The results shown in the main multiple-interaction models of Table 7 are subsequently explained by referring to these models and the *crossed multiple-interaction models* shown in Table A1 (Appendix A). In the case of *cover crops area*, farm management and farmer knowledge and perceptions of AES are found to influence their WTA. As regards to farm management, harvesting of ground olives (*Groundharv*) and previous participation in AES (*AESparticip*) were found to respectively increase and decrease farmer WTA for cover crops area. Regarding the former, the higher *Groundharv* is, the higher the IOG and ROG farmer WTA for a 1%-increase in cover crops area. This is shown in IOG_i model in Table 7 and the crossed model $ROG_{i\text{-}IOG}$ in Table A1, with the latter model being the six-interaction model combination used initially for IOG applied to the sample of ROG farms. The main reason for such an interaction is that, in general, farmers would not be willing to reach high levels of cover crops area as it would make it more difficult to harvest ground olives. For MOG, this interaction is not significant, suggesting that farmers of this sub-system do not find a high percentage of cover crops area particularly inconvenient for harvesting ground olives. As regards *AESparticip*, this interaction is only significant for MOG, which is currently the only sub-system with a considerable level of AES uptake. Previous participation in AES has been reported to positively impact farmers' enrolment (Hynes and Garvey 2009; Espinosa-Goded, Barreiro-Hurlé, and Ruto 2010). Regarding knowledge and perceptions, there is a positive interaction between the attribute cover crops area and ROG farmer knowledge of the cover crops requisite within cross-compliance (*KnowCC*), which is also consistent with earlier literature (Wynn, Crabtree, and Potts 2001).

Table 7. Main multiple-interaction models for the three olive grove sub-systems.

		MOG$_i$		ROG$_i$		IOG$_i$	
		Coef.	*S.e.*	*Coef.*	*S.e.*	*Coef.*	*S.e.*
Attributes & constant							
CCAR		-0.163*	0.023	-0.154***	0.028	-0.038*	0.017
CCMA		-5.367***	1.165	-8.277***	1.425	-2.303***	0.531
EFA		-2.676***	0.707	-0.977***	0.208	-0.621**	0.226
COLLE		-1.435***	0.023	-1.453**	0.496	-2.168***	0.413
MONI		0.012	0.659	-0.032	0.017	-0.009	0.012
PAYM		0.014***	0.002	0.012***	0.002	0.014***	0.001
ASC$_{SQ}$		-4.256	2.496	-6.091***	1.489	-1.110	0.887
Interactions							
CCAR x	*AESparticip*	0.073*	0.037				
	KnowCC			0.100**	0.031		
	Groundharv					-0.002***	0.000
CCMA x	*PerCCprofit*	0.878**	0.276	1.148**	0.348		
	Educa2					1.403*	0.682
EFA x	*PerEFAbenef*	0.454**	0.169				
	Oliarea10			0.611*	0.291		
	No-Training					-0.695*	0.279
COLLE x	*Oliarea20*	-2.474**	0.917				
	Age60			-5.179***	1.381		
	No-Takeover					1.187*	0.584
ASC$_{SQ}$ x	*Age*	0.123*	0.051				
	Freqadvi	-4.311*	1.778				
	Famlabour			0.036*	0.016		
	No-Training			2.146*	0.966		
	Oliarea20					-2.453**	0.910
	SPaym750					2.163*	0.946
St.dv. of the parameters							
CCAR		0.104***	0.019	0.090***	0.015	0.097***	0.016
CCMA		2.383***	0.532	5.110***	0.758	1.956***	0.397
EFA		1.424***	0.249	0.734**	0.238	0.867***	0.156
COLLE		2.478***	0.575	4.295***	0.591	1.706***	0.350
St.dv. latent random effects		5.015***	1.067	3.872***	0.534	3.519***	0.581
Goodness-of-fit							
LL		-356.8		-488.5		-496.5	
AIC		1.266		1.162		1.273	
BIC		1.400		1.260		1.378	
McFadden Pseudo-R^2		0.441		0.490		0.451	
Observations		74		109		101	

*, **, and *** denote significance at the 5, 1, and 0.1% levels, respectively. Each model includes six interactions, four with attributes and two with the ASC$_{SQ}$.

Source: Own elaboration.

With regards to *cover crops management*, farmer characteristics and perceptions are determinants of their preferences towards this attribute. In particular, as farmers' perception of cover crops as profitable in the long term (*PerCCprofit*) increases, their WTA for restrictive management of cover crops decreases, and this relationship is found in all three sub-systems – for $IOG_{i\text{-}MOG}$ at the 10% significance level. Therefore, farmers who perceive cover crops as a profitable farming practice would have fewer objections to restricting their cover crops management options. Similar findings are shown by Franco and Calatrava-Leyva (2010) and Rodríguez-Entrena, Arriaza, and Gómez-Limón (2014) for the adoption of soil conservation practices in olive growing. As regards farmer characteristics, in line with Siebert, Toogood, and Knierim (2006), WTA for restrictive management of cover crops fall when farmers have at least a secondary-school education (*Educa2*), although this is only reported for IOG.

Farmers' preferences towards *ecological focus areas* are also influenced by a variety of factors. In particular, not having undergone agricultural professional training (*No-Training*) increases the WTA for these areas in MOG and IOG. Similarly, Rodríguez-Entrena and Arriaza (2013) found a positive influence on the adoption of environmentally-friendly practices by trained olive growers. Farm size (*Oliarea10*) is also shown to reduce (ROG) farmer WTA for EFA A possible explanation for this result is that there seem to be fewer difficulties when large farms have to use part of their farmland as ecologically focused areas (Schulz, Breustedt, and Latacz-Lohmann 2014; Grammatikopulou, Pouta, and Myyrä 2015). In addition, the higher the farmer perception of EFA being environmentally beneficial (*PerEFAbenef*), the lower the WTA for these areas in MOG. Since environmental benefits become more apparent on steep slopes, it is not incidental that this interaction was found to be significant for MOG but not for the plain sub-systems.

Farm and farmer characteristics and farmer perceptions play a role in farmers' preferences towards *collective participation* as well. With regards to farm characteristics, farm size (*Oliarea20*) negatively affects farmer willingness to participate in collective AES. This contrasts with the abovementioned positive interaction between farm size and EFA, although the interaction with EFA is only significant for ROG and the interaction with the attribute collective participation is significant for MOG and IOG. As farmers typically look for groupings with other similar farmers (Franks 2011), the smaller number of large farms makes it more difficult to create a collective. Regarding farmer characteristics, farmers over 60 years old (*Age60*) show a higher WTA for collective participation than younger ones. This is found in two sub-systems (ROG and IOG) and is in line with the earlier results of Hynes and Garvey (2009) and Ruto and Garrod (2009). Regarding farmer perception, it appears that when farmers think there will be no farm takeover (*No-Takeover*), they are more willing to participate in AES collectively and their WTA is reduced. In this regard, Ruto and Garrod (2009) also found that farmers prefer not to encumber a successor with an AES contract they have negotiated. Yet, this interaction is only found for IOG farmers, suggesting that this may be a case-specific relationship.

The interactions with the ASC_{SQ} provide further information about what factors influence farmers' general willingness to participate in AES. We find a group of farm and farmer characteristics that significantly determine this general willingness. With regards to farm characteristics, the variables significantly interacting with the ASC_{SQ} are farm size (*Oliarea20*), the percentage of family labour over the total farm labour (*Famlabour*), and receiving an average single payment of over €750/ha (*SPaym750*). The interaction with farm size is negative for $ROG_{i\text{-}IOG}$ and IOG_i, which means that those ROG and IOG farms with more than 20 ha of olive groves (*Oliarea20*=1) are less willing to choose the status quo, thus increasing their willingness to participate in the schemes. On the contrary, the positive interaction with the variable family labour found for ROG_i reflects the fact that as the share of family labour increases, farmer willingness to participate in these schemes decreases, which is consistent with the results of Rodríguez-Entrena and Arriaza (2013). The effect of the single payment is not clear as the related interaction is negative in ROG $_{i\text{-}IOG}$ and positive in IOG_i. With respect to the latter, earlier literature identifies the competition of other CAP subsidies as a limiting factor for AES participation (Uthes and Matzdorf 2013). However, AES do not compete with but are complementary to single payment, meaning that further research about this point is called for. As to farmer characteristics, the variables that significantly interact with the ASC_{SQ} are the age of the farmer (*Age*), asking for professional advice (*Freqadvi*), and *No-Training*. Mirroring previous research (Hynes and Garvey 2009; Ruto and Garrod 2009; Grammatikopulou, Pouta, and Myyrä 2015), the interaction with *Age* is positive in the three sub-systems – in $ROG_{i\text{-}MOG}$ at the 10% significance level – meaning that older farmers are generally less willing to participate in these schemes. The interaction ASC_{SQ}×*Freqadvi* is negative in MOG_i and $IOG_{i\text{-}MOG}$ meaning that MOG and IOG farmers who frequently ask for professional advice are more willing to participate in these schemes, which is also highlighted in Siebert, Toogood, and Knierim (2006). Also, the interaction ASC_{SQ}×*No-Training* is positive in ROG_i and $IOG_{i\text{-}ROG}$, indicating that ROG and IOG farmers who have not undergone professional agricultural training are less willing to participate in AES. This result coincides with that found by Ducos, Dupraz, and Bonnieux (2009) for a number of EU countries.

3.3. Policy implications

Results show that there is significant inter and intra sub-system heterogeneity of farmers' preferences towards AES, both in general and specifically related to scheme attributes. Significant sub-system heterogeneity means that an action-based AES implemented equally (and with uniform payment) across an entire agricultural system would be an inefficient way to improve the provision of public goods. Ways of increasing the efficiency of the schemes –

better dealing with (inter and intra sub-system) farmers' heterogeneity – include the use of auctions (Rolfe, Windle, and McCosker 2009) and the result-oriented approach (Burton and Schwarz 2013). Auction mechanisms have the advantage of cost-revelation, which is of paramount importance due to the typically large heterogeneity of farmers, and can be used for procuring public-savings. However, they often show higher transaction costs from the public and private perspectives (Latacz-Lohmann and Van Der Hamsvoort 1998). The result-oriented approach provides greater flexibility than the action-based approach to achieve the same environmental outcome and encourages farmers to innovate more, though it likely entails higher transaction costs (especially related to monitoring) as well (Burton and Schwarz 2013)[5]. While these approaches are still open to further research, they stand out as promising options for the more efficient design of agri-environmental incentives, especially when there is a large heterogeneity of farmers, as is the case in this study. In particular, we recognise that the implementation of collective AES using these approaches requires further investigation.

The results related to intra sub-system heterogeneity of farmers' preferences towards AES provide further valuable information for policy-making. According to our results, there are a number of socioeconomic factors common to the three olive grove sub-systems that the policy-maker can make use of to improve scheme efficiency in terms of incentivising the production of public goods. In particular, improving farmers' agricultural training and their knowledge and perception of the provision of environmental public goods – e.g. with awareness campaigns, seminars, etc. – facilitates scheme uptake in all three sub-systems. Age is another factor that is common to the three sub-systems, showing a negative relationship with farmers' willingness to participate in AES. In light of this, facilitating farm succession to young farmers would be a good policy option, although this is often difficult due to ageing issues in rural areas.

Farm size is another factor common to the three sub-systems, although it is worth discussing its role in scheme uptake. First, it must be noted that there is no consensus in the specialised literature with regards to this issue (Defrancesco et al. 2008). Although works that found a positive relationship between farm size and the adoption of AES are more common (Falconer 2000; Ducos, Dupraz, and Bonnieux 2009; Ruto and Garrod 2009), there are also works that reported either no relationship or a negative relationship between them (Defrancesco et al. 2008; Espinosa-Goded, Barreiro-Hurlé, and Ruto 2010). Interestingly, our results partly support both findings. Although we find a positive relationship between farm size and the adoption of AES in general, we also find that farm size can have either a positive or negative influence depending on the specific attribute under consideration. In particular, our results show that farm size positively affects farmer willingness to adopt EFA as a requirement of AES, and negatively affects farmer willingness to participate in collective

[5] Obviously, result-oriented schemes can be implemented using auctions that establish scheme levels in terms of the environmental outcome rather than with respect to prescribed practices, as action-based schemes do.

schemes. Like Falconer (2000) and Ruto and Garrod (2009), we believe that there is a strong case for considering the relationship between farm size and AES uptake as unambiguously positive in a general setting. The higher economies of scale and comparatively lower per-hectare transaction costs of larger farms strongly support this statement. Yet, according to our results, specific attributes of the schemes can either reinforce or counteract this general positive relationship; EFA and collective participation, respectively, are good examples of those two possibilities. As regards EFA, it is easier for large farms to allocate their worst land – associated with lower opportunity costs – to comply with the EFA requirement. Schulz, Breustedt, and Latacz-Lohmann (2014) and Grammatikopoulou, Pouta, and Myyrä (2015) revealed similar findings. In fact, the authors of the first study warned about possible transfers of EFA between farmers as a result of their different participation costs. Hence, policy makers should bear this in mind if they want to ensure that the EFA requirement is not largely fulfilled by means of land transfers between farms (e.g. from MOG to ROG and IOG, and from large to small farms), otherwise the inclusion of this requirement could fail to promote an effective increase in environmental performance. Regarding collective participation, a plausible reason for this negative relationship could be the greater difficulty in grouping farmers with similar characteristics. Accordingly, grouping facilitators should take this into account when attempting to create collectives.

In addition, there are other factors that seem to be sub-system specific. Generally speaking, it is costly to gather this type of sub-system specific information, so the policy-maker should consider whether or not the effort would be justified. The use of local stakeholders (as recommended by Hart et al. 2011; Uthes and Matzdorf 2013; and Villanueva et al. 2014, among others), would probably facilitate this decision by providing further information at sub-system level.

4. Conclusions

An extensive literature confirms that farmers' preferences towards AES are heterogeneous. To our knowledge, this is the first study that shows this heterogeneity at the sub-system level. To do so, a choice experiment method was used to analyse farmers' preferences towards AES in the case study of three olive grove sub-systems (extensive, intermediate, and intensive) in southern Spain. Our results reveal inter and intra sub-system heterogeneity of farmers' preferences towards AES both in general and specifically related to scheme attributes. There seems to be a variety of factors behind inter sub-system heterogeneity, especially those associated with sub-system specificities (mainly, the different joint production). However, further research is needed to provide evidence on how and to what extent such specificities influence farmers' preferences towards AES.

Intra sub-system heterogeneity also shows a wide variety of factors influencing farmers' preferences towards these schemes, most of them related to farm/farmer socioeconomic factors and, to a lesser extent, physical farm factors. We find some of these factors (age, training, farmer perception of the practices included in the scheme, and farm size) influence farmers' preferences towards AES regardless of the sub-system, while a number of additional factors (advisory frequency and the presence of certain conflicting practices) exert an influence in more than one sub-system. Additionally, there are other factors specific to each sub-system, which are clearly related to structural characteristics of the farm. In just a few cases, we have also found a factor that can exert either a positive or negative influence depending on the attribute under consideration. Worthy of mention is the farm size factor, where although results show a generally positive relationship with AES uptake, it can also positively (negatively) affect farmer willingness to adopt EFA as a requisite of (to participate in collective) AES. All these results call for the careful consideration of not only agricultural sub-system specificities, but also farm/farmer characteristics and farmer knowledge and perception, in order to design schemes that efficiently promote the production of environmental public goods.

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Appendix A. Crossed models

Table A1. Crossed multiple-interaction models across sub-systems.

		$MOG_{i\text{-}ROG}$		**$MOG_{i\text{-}IOG}$**		**$ROG_{i\text{-}MOG}$**		**$ROG_{i\text{-}IOG}$**		**$IOG_{i\text{-}MOG}$**		**$IOG_{i\text{-}ROG}$**	
		Coef.	*S.e.*	*Coef.*	*S.e.*	*Coef.*	*S.e.*	*Coef.*	*S.e.*	*Coef.*	*S.e.*	*Coef.*	*S.e.*
Attributes & constant													
	CCAR	-0.041	0.036	-0.106***	0.022	-0.084***	0.017	-0.078***	0.018	-0.108***	0.016	-0.105*	0.043
	CCMA	-5.000***	1.226	-2.324***	0.475	-7.531***	1.541	-5.369***	0.764	-3.173***	0.857	-3.594**	1.089
	EFA	-0.875***	0.208	0.135	0.511	-1.422*	0.557	-1.122**	0.361	-0.885	0.525	-0.961***	0.265
	COLLE	-2.310***	0.523	-1.635**	0.616	-1.957***	0.535	-2.154***	0.628	-1.201**	0.452	-1.981***	0.433
	MONI	0.010	0.016	0.018	0.018	-0.029	0.017	-0.035	0.018	-0.011	0.012	-0.008	0.013
	PAYM	0.013***	0.002	0.016***	0.002	0.013***	0.001	0.013***	0.001	0.013***	0.001	0.014***	0.001
	ASC_{SQ}	-0.975	1.526	-0.181	0.696	-3.615*	1.569	-0.174	0.679	-5.056	2.732	-1.621	1.091
Interactions													
CCAR×	*AESparticip*					0.000	0.056			0.032	0.038		
	KnowCC	-0.071	0.042									-0.008	0.046
	Groundharv			-0.001	0.001			-0.002*	0.001				
CCMA×	*PerCCprofit*	0.830**	0.302			0.759	0.417			0.396	0.214	0.474	0.257
	Educa2			-0.728	1.125			-0.190	1.121				
EFA×	*PerEFAbenef*					0.171	0.142			0.005	0.123		
	Oliarea10	0.398	0.337									0.137	0.328
	No-training			-1.487**	0.567			0.236	0.406				
COLLE×	*Oliarea20*					-0.001	0.921			-1.225*	0.562		
	Age60	0.728	0.979									0.723	0.835
	No-takeover			-1.296	0.893			-0.104	1.020				
ASC_{SQ}×	*Age*					0.052	0.030			0.112*	0.054		
	Freqadvi					-1.100	0.800			-2.123*	1.020		
	Famlabour	-0.005	0.022									0.005	0.016
	No-training	2.206	1.480									2.009	1.059
	Oliarea20			-0.803	1.555			-2.649**	0.882				
	SPaym750			2.252	1.765			-3.473***	0.977				

Table A1. (*Continued*)

	$MOG_{i\text{-}ROG}$		$MOG_{i\text{-}IOG}$		$ROG_{i\text{-}MOG}$		$ROG_{i\text{-}IOG}$		$IOG_{i\text{-}MOG}$		$IOG_{i\text{-}ROG}$	
	Coef.	*S.e.*	*Coef.*	*S.e.*	*Coef.*	*S.e.*	*Coef.*	*S.e.*	*Coef.*	*S.e.*	*Coef.*	*S.e.*
St.dv. of the parameters												
CCAR	0.108***	0.026	0.138***	0.030	0.087***	0.015	0.094***	0.017	0.120***	0.018	0.118***	0.020
CCMA	1.974***	0.560	2.124***	0.432	4.078***	0.661	4.864***	0.733	1.826***	0.337	2.163***	0.338
EFA	1.458***	0.258	1.589***	0.288	0.796**	0.256	1.273***	0.296	0.840***	0.164	0.911***	0.169
COLLE	2.299***	0.579	2.363***	0.496	3.522***	0.504	3.860***	0.454	1.684***	0.396	2.546***	0.428
St.dv. latent random	4.254***	0.686	3.275***	0.639	3.656***	0.566	3.964***	0.612	3.653***	0.637	4.586***	0.758
Goodness-of-fit												
LL	-364.5		-368.9		-510.3		-507.9		-498.6		-482.3	
AIC	1.310		1.307		1.190		1.184		1.279		1.276	
BIC	1.445		1.440		1.287		1.281		1.383		1.383	
Pseudo-R^2 McFadden	0.432		0.433		0.477		0.479		0.438		0.440	
Observations	73		74		111		111		101		98	

*, **, and *** denote significance at the 5, 1, and 0.1% levels, respectively. Each model includes six interactions, four with attributes and two with the ASC_{SQ}.

Source: Own elaboration.