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Optimal Design of Agri-environmental Schemes under Asymmetric Information for Improving Farmland Biodiversity

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Abstract

Information asymmetry is one of the main obstacles to the effective design and implementation of agri-environmental schemes (AES). The literature has generally addressed this issue through the use of principal-agent models (PAM). We develop a PAM to support optimal design of a new AES for improving farmland biodiversity. We use the results of choice experiments to assess both the costs incurred by the agent for the provision of biodiversity and the resulting social benefits. We also make a number of novel contributions such as the inclusion of a non-linear non-compliance detection curve, a sensitivity analysis to identify which parameter estimates have a critical impact on PAM results, and analysis of the efficiency of different sanction scenarios. The results suggest that: (i) the second-best solutions differ significantly from the optimal solutions attainable with perfect information, with farmers being strongly over-compensated for the extra costs associated with improved biodiversity; (ii) monitoring levels should be higher; (iii) the sanction system should be tougher. Sensitivity analysis shows the need for accurate estimates of the marginal cost of public funds and the costs and benefits associated with the public goods, which represent the key parameters determining PAM results.

Keywords: *Common Agricultural Policy*; *moral hazard*; *mountain olive groves*; *principal-agent model*; *public goods*.

JEL classifications: *Q18, Q11, Q25*.

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1. Introduction and Objectives

Ensuring the adequate provision of public goods by the agricultural sector has become one of the main policy objectives for the sector. To meet that objective, a number of instruments have been designed and implemented, encompassed within agri-environmental policy (OECD, 2015).

One of the most notable policy instruments that can be used to ensure the adequate provision of public goods by agriculture is agri-environmental measures (OECD, 2010; Hart *et al.*, 2011). These measures comprise a system of voluntary incentives for farmers who sign multi-year contracts with the public administration, as typified by agri-environmental schemes (AES) included in the second pillar of the Common Agricultural Policy (CAP). Under the terms of these contracts, farmers commit to employing a set of specific agricultural practices aimed at improving (or maintaining) the level of provision of environmental public goods, in exchange for an annual payment per unit area that compensates for lost profits, additional costs and transaction costs incurred due to the implementation of these practices (Uthes and Matzdorf, 2013).

The effective design of AES aimed at improving the production of public goods poses a real challenge for policy-makers, because of the major information gaps regarding the costs and benefits of implementing these instruments and their voluntary nature (Westhoek *et al.*, 2013). In particular, information asymmetry can significantly reduce the efficiency of these measures (Blandford, 2007). It is difficult to distinguish between potential beneficiaries of these contracts on the basis of actual compliance costs. This gives rise to the problem known as *adverse selection* (or 'hidden information'), allowing producers to sign contracts that overcompensate the costs of compliance incurred. On the other hand, these measures also face difficulties in terms of monitoring farmers' level of compliance with the contracts they signed, since it is not feasible to audit the individual compliance of all the beneficiaries (perfect monitoring). This gives rise to the *moral hazard* problem (or 'hidden actions'), which means that some of the farmers that benefit from these measures decide not to comply with the programme obligations.

Both problems have been extensively analysed in the literature, especially through the use of principal-agent models (PAM) (Laffont and Martimort, 2009), where the administration managing the measures is considered the 'principal', characterised as having incomplete information on the real costs incurred by farmers, who act as 'agents'. The papers that have analysed the problems of adverse selection with relation to AES include Moxey *et al.* (1999), Viaggi *et al.* (2009) and Quillérou and Fraser (2010). In addition, the problem of moral hazard in the implementation of these measures has been analysed in Choe and Fraser (1999), Hart and Latacz-Lohmann (2005), Ozanne and White (2008), Bartolini *et al.* (2012) and Fraser (2013). It is also worth highlighting the studies that jointly consider the two problems, such as Melkonyan and Taylor (2013) and White and Hanley (2016). Interested readers can also consult Fraser (2015), where a comprehensive collection of papers in this field is compiled.

All these studies have attempted to analyse the available tools that the administration can use to minimise these two problems, and thus increase the efficiency of the measures. In any case, almost all studies to date analyse these issues from an essentially theoretical perspective, using applications based on parameters whose values are assumed for explorative numerical analyses. In this respect, the main novelty of this study is that it takes an applied approach to provide practical, realistic support for the

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design and implementation of a new AES. More specifically, the objective of the research is to build and exploit a PAM to support decision-making for the optimal design of a new scheme aimed at improving biodiversity in Andalusian mountain olive groves (MOG). The model takes into account the information resulting from two valuation exercises relating to the biodiversity provided by this agricultural system: one on supply (the costs of provision incurred by the olive growers) and the other on demand (the welfare gains due to improvements in the provision).

No previous studies have used a PAM with specific private cost functions and social benefit functions obtained for the proposed AES, as we do here. We also note that most of the related applications to date have focused on the design of agri-environmental contracts aimed at reducing public ‘bads’, such as diffuse pollution. There are no studies that address the adequate provision of biodiversity by agricultural systems, with the single exception of White and Hanley (2016). We also include three additional features: non-linear non-compliance detection curves; sensitivity analysis to assess how estimated values of key affect optimal AES design; and analysis of different sanction scenarios for non-compliance.

Section 2 presents the Andalusian MOG agricultural system, as well as the proposed AES targeted at improving the provision of biodiversity. Section 3 describes the PAM built to analyse the optimal design of the proposed scheme, while section 4 explains the empirical specification of the model, justifying the parameter value estimates used. Section 5 presents the main results based on the most reliable parameter estimates. Section 6 discusses the results of the sensitivity analysis and examines the effect of more stringent sanctions systems for non-compliance. Section 7 outlines the conclusions drawn from the findings.

2. AES for Promoting Biodiversity in Mountain Olive Groves

2.1. Andalusian mountain olive groves

Olive groves cover 1.52 million hectares in Andalusia (more than 30% of the total agricultural area), making this crop a key generator of income and employment in the rural areas. The olive groves in Andalusia are heterogeneous, with a wide range of different systems, including the so-called ‘mountain olive groves’ (MOG). This type of olive grove is typically located on steep slopes in poor, shallow soils, resulting in low yields. This, along with the high production costs due to the difficulties of mechanisation, makes it an agricultural system with low economic profitability and at high risk of abandonment.

For our purposes, the MOG are characterised as growing under rainfed conditions in areas with slopes of 15% or more, and average olive yields equal to or less than 2,500 kg/ha. Thus defined, MOG cover 211,000 hectares in Andalusia, representing about 14% of the total area of olive groves in the region.

The low profitability of the activity and the difficulties in employing mechanised farming methods in this type of olive grove make it an extensive, ‘high nature value’ farming system (Paracchini *et al.*, 2008). Indeed, the low-intensity work and limited use of agrochemicals, together with the maintenance of long-standing plantations and traditional elements such as walls, hedges, riparian vegetation, etc. have enabled this system to continue providing environmental public goods, especially those related to biodiversity (Stroosnijder *et al.*, 2008). However, the provision of the biodiversity public good by this agricultural system is under threat due to both the intensification

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processes aimed at improving productivity and profitability, and the abandonment of agricultural activity on those lands (Rocamora-Montiel *et al*., 2014). Market failure occurs when the level of biodiversity production is suboptimal from a public perspective, related to the growing social demand for it (Rodríguez-Entrena *et al*., 2014). In this case, a new AES that encourages the use of agricultural practices can be justified to improve the provision of the biodiversity public good (Villanueva *et al*., 2015, 2017b).

2.2. Proposal for a new AES aimed at improving biodiversity

Numerous studies have demonstrated the high potential of olive grove systems to improve biodiversity (for a literature review, see Carmona-Torres *et al*., 2016; Rocamora-Montiel *et al*., 2014; Villanueva *et al*., 2015). These studies have identified soil management practices and phytosanitary treatments as some of the most important elements for olive growers to improve, from an agri-environmental perspective. As such, an AES aimed at improving the biodiversity of the MOG should be designed that promotes the use of cover crops and the correct choice and dose rates of biocides.

Initially, agricultural abandonment was thought to be another option for improving the biodiversity in this case study. However, it was not included because AES promoting land abandonment is not on the policy agenda, given the doubts about its real positive impact on biodiversity and the fact that it would probably involve a reduction in the provision of social public goods such as rural vitality, landscape and cultural heritage.

A possible AES might consist of five-year contracts, through which olive growers would commit to employing a set of practices to improve the provision of biodiversity, in exchange for an annual per-hectare payment. These agri-environmental contracts establish certain levels of stringency for three variables: cover crop area (CCA); cover crop management (CCM); and insecticide treatment (INT). These practices have a major influence on biodiversity in MOG land, especially on bird richness, with less intensive use of these practices usually resulting in positive effects (Duarte *et al*., 2009). The levels of these three variables are set in an attempt to include a variety of practices associated with different levels of provision of the biodiversity public good, from the minimum level required by cross-compliance, to the most demanding level. In practical terms, five alternative designs or scenarios for AES application have been proposed, with increasingly stringent requirements, as shown in Table 1 (further details can be consulted in Villanueva *et al*., 2017a).

Once the different AES designs had been established, secondary information sourced from scientific publications can be used to quantify the biodiversity provided by MOG for each of the AES scenarios considered. Since bird richness represents one of the most suitable indicators to quantify biodiversity (EEA, 2010), we use the number of bird species per 10 hectares of MOG. However, as the average size of MOG farms is around 10 hectares, this indicator has been termed as bird species per farm, to make it more easily understandable (see Villanueva *et al*., 2017a, for a more comprehensive explanation). Table 1 summarises the levels of provision set in each case.

The proposed AES generates problems of information asymmetry. However, the administration can easily collect information about agricultural production technologies and costs for a wide range of farms, so the administration managing the AES can be considered to have complete information about farmers' compliance costs. In this case, there is no hidden information or adverse selection problems, so we focus on the moral hazard (hidden actions) problem.

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Table 1
Level of biodiversity provision by mountain olive groves (MOG) for the AES scenarios considered

AES scenario	Level of stringency	Bird species/farm (no.)	Increase in bird species/farm (no.)
Minimum level required (cross-compliance)	CCA: 10% of the MOG area under cover crops CCM: free management INT: free treatment	7.8	0.0
Integrated production	CCA: 30% of the MOG area under cover crops CCM: restricts the use of herbicides (they can be used in two of the five years) and tillage (only shallow tillage is allowed) INT: limited treatment (dimethoate and copper oxychloride are not allowed)	13.0	5.2
Integrated production plus	CCA: 50% of the MOG area under cover crops CCM: management using only mower or animal grazing INT: limited treatment (dimethoate and copper oxychloride are not allowed)	17.6	9.8
Ecological production	CCA: 50% of the MOG area under cover crops CCM: management using only mower or animal grazing INT: only treatments used in organic production	19.8	12.0
Ecological production plus	CCA: 100% of the MOG area under cover crops CCM: management using only mower or animal grazing INT: only treatments used in organic production	23.6	15.8
Provision of environmental public goods	CCA: 100% of the MOG area under cover crops CCM: non-management, except mowing or grazing the cover crops early in the summer to reduce fire risk INT: non-treatment (use of any biocidal product is prohibited)	30.0	22.2

Source: Villanueva *et al*. (2017a).

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3. Principal-agent Modelling[2]

3.1. Farmer decision-making model

Farmers' decision-making in relation to AES can be assumed to take place in two successive stages (Ozanne *et al.*, 2001). The first is where the farmer decides whether or not to take part in the scheme by signing the corresponding contract. It is during this first stage that the problem of adverse selection can arise. If the farmer does decide to take part, the second decision regards the extent to which he will comply with the contract, that is, the degree of compliance with the conditions stipulated by the scheme. This is where moral hazard problems can appear.

Farmer i makes the first of the two decisions by comparing the amount of the agri-environmental payments (p_t, quantified for the year t in current euros/hectare) with the costs ($\psi_{it}(B)$, also quantified for the year t in current euros/hectare) that would be incurred for increasing the provision of the biodiversity public good to the agreed level (B represents this increase and is expressed as the number of bird species/farm) throughout the contract period (Fraser, 2012). Assuming a behaviour that maximises the expected utility of profit,[3] the farmer decides to take part in the scheme only if the rationality or participation constraint is satisfied:

$$E\left[U\left(\sum_t \delta_t\ p_t\right)\right] \geq E\left[U\left(\sum_t \delta_t\ \psi_{it}(B)\right)\right] \tag{1}$$

where E is the expected value operator, U is the utility function representing farmer i's risk preferences, and δ_t is the discount factor for year t. Considering that p_t and $\psi_{it}(B)$ are known in advance for the farmer (i.e. they are non-random parameters) and utility is a monotonic function, expression (1) can be simplified as follows:

$$\sum_t \delta_t\ p_t - \sum_t \delta_t\ \psi_{it}(B) \geq 0. \tag{2}$$

when this constraint is satisfied, the farmer signs the corresponding agri-environmental contract. The farmer (acting as the 'agent') is then faced with a moral hazard, deciding each year on the degree of compliance with the requirements of the contract. This variable, which we denote c_{it}, expresses contractual compliance for the year t, ranging from 0 (indicating total breach of the contract) to 1 (indicating perfect compliance). In our case study, the level of compliance is quantified to represent the increase in the effective provision of biodiversity by the farmer i compared to the required increase in the provision (B) in order to reach the level stipulated in the contract. Thus, the effective improvement in the level of provision of the public good for each farm i the year t can be defined as $b_{it} = c_{it}B$, quantified by the number of bird species/farm.

[2]Although the model built is aimed at supporting the design and implementation of the proposed AES to improve biodiversity in MOG, it is worth mentioning that this modelling approach can be easily adapted to any AES aiming to improve the provision of other public goods.

[3]Taking into account the fact that there is strong evidence that most producers are risk-averse, any simplification assuming expected profit maximising behaviour (i.e. farmers' risk neutrality) could lead to biased results. This has been analysed by Fraser (2002, 2004) and Ozanne *et al.* (2001) demonstrating that assuming risk neutrality tends to lead to an exaggeration of the importance of moral hazard.

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The farmer assesses the effects of his potential non-compliance, taking into account the probability that the public administration (acting as the 'principal') will detect the breach of contract and that the agent will be sanctioned. This probability depends on the intensity of the monitoring carried out by the administration and on the farmer's degree of compliance (Bartolini *et al.*, 2012):

$$\text{Probability that the principal detects non-compliance in year } t\text{: } m_t\theta(c_{it}) \tag{3}$$

$$\text{Probability that the principal does not detect non-compliance in year } t\text{: } 1 - m_t\theta(c_{it}) \tag{4}$$

where m_t is a bounded continuous variable [0,1] that measures the percentage level of monitoring of the scheme (number of inspections over the total number of farms) in each year t, and $\theta(c_{it})$ is a function of the probability of detecting non-compliance with the scheme, which depends on c_{it}.

We assume that the farmer tries to maximise the expected utility of profit associated with participation in AES throughout the contract period, quantifying it each year as a weighted sum of the utility of profit when the principal does not detect possible non-compliance (payment less the cost of effective provision of the public good) and the utility of profit when this non-compliance is detected (payment less the sanction for non-compliance and less the cost of effective provision of the public good):

$$\begin{aligned}&\max_{c_{it}} \sum_t \delta_t\ E[U(\pi_{it})]\\ &= \sum_t \delta_t[(1 - m_t\ \theta(c_{it}))\ U[p_t - \psi_{it}(c_{it}B)] + m_t\ \theta(c_{it})\ U[p_t(1 - \rho_t(c_{it})) - \psi_{it}(c_{it}B)]]\end{aligned} \tag{5}$$

where $\rho_t(c_{it})$ is a continuous dimensionless variable that quantifies the sanction for non- compliance in year t as a percentage of the agri-environmental payment.

The solution to the optimisation problem (5) can be obtained through the corresponding first-order condition:

$$\frac{\partial\left[\sum_t \delta_t\ E[U(\pi_{it})]\right]}{\partial c_{it}} = 0. \tag{6}$$

It is evident that in this optimisation problem, the parameters B, p_t, m_t and $\rho_t(c_{it})$ are exogenous to the farmer, since he/she has no control over them. However, they are decision variables for the public administration, as will be analysed below.

3.2. Public administration decision-making model

Taking into account the behaviour of the farmers, the decision problem for the administration is to design the policy instrument under analysis (AES) so that its real-world implementation maximises social welfare. The decision variables for the administration are B, p_t, m_t and $\rho_t(c_{it})$.

We consider a different AES application for diverse groups of farmers with similar compliance costs, thus analysing differences in the variables B_i, p_{it} and m_{it} for each group or class i. This is justified by the fact that a differentiated application (a range of different contracts) can provide better results from a public perspective. The

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sanction system ($\rho_t(c_{it})$) is considered to be the same for all groups of farmers for reasons of fairness in political terms.

The principal's decision problem now centres on maximising the social welfare function (Z) subject to a series of constraints marked by the strategic behaviour of the farmers. Assuming this regulator is risk neutral (Moxey *et al.*, 1999; Ozanne *et al.*, 2001; White and Hanley, 2016), this optimisation problem can be expressed algebraically as follows:

$$\begin{aligned}\max_{\gamma_i, B_i, p_{it}, m_{it}} Z &= \sum_t \sum_i \delta_t \gamma_i w_i \, z_{it} \\ &= \sum_t \sum_i \delta_t \gamma_i w_i \begin{bmatrix} v_{it}(c_{it}B_i) - \psi_{it}(c_{it}B_i) - p_{it} \, (\lambda - 1) \\ + \, p_{it} \, m_{it} \, \theta(c_{it}) \, \rho_t(c_{it}) \, (\lambda - 1) - M(m_{it}) \, \lambda \end{bmatrix}\end{aligned} \tag{7.1}$$

$$\text{s.t.} \sum_t \delta_t \, p_{it} - \sum_t \delta_t \, \psi_{it}(B_i) \geq 0 \qquad \forall i \tag{7.2}$$

$$\gamma_i \left[\frac{\partial \sum_t \delta_t \, E[U(\pi_{it})]}{\partial c_{it}} \right] = 0 \qquad \forall i. \tag{7.3}$$

The social welfare function (7.1) can be decomposed into five components. The first term ($v_{it}(c_{it}B_i)$) corresponds to the benefit to society in year t resulting from the improvement in the effective provision of the biodiversity as a consequence of the implementation of the scheme (the increase in the provision from the current level to $b_{it} = c_{it}B_i$) measured in current euros.

The second term of the social welfare function refers to farmers' private costs resulting from participation in the scheme the year t ($\psi_{it}(c_{it}B_i)$).

It should be noted that the budgetary resources needed to implement public spending policies (such as the AES) must first be collected through the tax system, and this inevitably causes distortions that reduce economic efficiency (Auerbach and Hines, 2002). The distortions introduced by the tax system can be quantified through the marginal cost of public funds (MCF, denoted as λ), a synthetic measure intended to reflect the shadow price that society pays for each euro invested in any public spending policies (Dahlby, 2008).[4] Thus, the third component of the social welfare function ($p_{it} \, (\lambda - 1)$) represents the social cost of the budget allocation spent on the proposed AES in year t, taking into account the inefficiency introduced by the tax system.

The fourth term of expression (7.1) accounts for the welfare gain derived from the imposition of sanctions for non-compliance, considering both the budgetary savings ($p_{it} \, m_{it} \, \theta(c_{it}) \, \rho_t(c_{it}) \, \lambda$) and the farmers' income lost ($p_{it} \, m_{it} \, \theta(c_{it}) \, \rho_t(c_{it})$) as a result of these sanctions.

The last term of the objective function refers to the cost of monitoring the scheme ($M(m_{it})$), which must also be multiplied by λ because, since it is financed through the public budget, it also generates an additional cost due to the inefficiency of the tax system.

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[4]Before agri-environmental payments can be made, the total amount must first be collected by the public sector through the tax system. In this sense, collecting 100 monetary units through taxes involves an additional amount of money, say X monetary units, because of the tax distortion caused on the whole economic system. Accordingly, the marginal cost of public funds can be roughly represented as the ratio $(100 + X)/100$.

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The social welfare function (expression 7.1) is expressed as a weighted sum of the different farm types participating in the proposed AES. In this respect, γ_i is a binary variable: 1 when farm type i participates in the scheme; 0 when that farm type does not participate. In addition, w_i represents the percentage of the area of farm type i over the total area eligible to participate in the scheme.

The public administration's decision problem is subject to two constraints. The first (expression (7.2)) refers to the participation constraint derived from expression (2). The second (expression (7.3)) refers to the optimality condition of the farmers' decisions according to their level of compliance, derived from expression (6).

4. Empirical Specification

Considering a standard AES implementation, the general model proposed above is simplified by assuming that agri-environmental payments, percentage levels of monitoring and sanctions remain constant throughout the whole contract period: $p_{it} = p_i$, $m_{it} = m_i$ and $\rho_t(c_{it}) = \rho(c_{it})$, respectively. Pragmatic (simplicity) and budgetary reasons are usually given as justification for this common policy practice.

4.1. The cost of provision of biodiversity of MOG farmers

In order to account for the heterogeneity of farmers in the optimal design of the AES, it is appropriate to group the population of target farmers into a smaller number of representative classes or groups. Given the purpose of our analysis, it is evident that farmers should be classified according to the cost of providing biodiversity, $\psi_{it}(c_i B_i)$. The data used for this purpose have been collected recently for a valuation exercise concerning the provision of public goods by Andalusian MOG farmers, as part of the European project that provides the framework for this research (PROVIDE Project: http://www.provide-project.eu), in which 261 farmers were surveyed (Villanueva *et al.*, 2017c). This valuation exercise used choice experiment techniques, with the attributes and levels of stringency described in Table 1. From this, we determine willingness to accept (WTA) agri-environmental contracts set out as alternative AES scenarios, quantified in euros/hectare/year. We assume that these WTA values are equivalent to the costs of providing the increased level of biodiversity corresponding to each type of proposed contract.

To group farmers according to the costs they incur for providing biodiversity (i.e. WTA), the latent class model (LCM) was used as the econometric specification (see Annex 4 of Villanueva *et al.*, 2017c, which shows the LCM specification used). This model accounts for discrete parameter distribution, assuming that there are certain latent classes of individuals that share similar patterns of preferences (Hess *et al.*, 2011).

The results of this valuation exercise (Villanueva *et al.*, 2017c) reveal the existence of two classes of mountain olive farmers, clearly differentiated according to their costs of provision, with Class 1 showing lower WTA for signing the proposed AES contracts (and therefore relatively low biodiversity provision costs), and Class 2 showing higher WTA (thus higher costs of provision of this public good). Class 1 represents 59.5% of the mountain olive farmers under study ($w_1 = 0.595$), while Class 2 covers

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the rest (w_2 = 0.405). The main factor explaining this difference in costs of provision is the yield (i.e. opportunity cost of the income foregone if the AES requirements are fulfilled).

The results of the LCM enabled the calculation, for each class, of the WTAs for signing the different contracts for the proposed AES (shown in Table 1) at the beginning of the contract period (t = 0), as shown in Table 2.

From the point estimates for the different AES alternatives, regressions were run to fit these points to quadratic functions, which represent the biodiversity provision curves in each class. As can be seen in Figure 1, the goodness of fit is satisfactory (R^2 = 0.988 for Class 1 and R^2 = 0.996 for Class 2). Thus, the functions $\psi_{1,0}(b_{1,0})$ and $\psi_{2,0}(b_{2,0})$ to be used in the proposed PAM are as follows:

$$\psi_{1,0}(b_{1,0} = c_{1,0}B_1) = 0.54\ b_{1,0}^2 + 0.45\ b_{1,0} \tag{8.1}$$

$$\psi_{2,0}(b_{2,0} = c_{2,0}B_2) = 2.08\, b_{2,0}^2 + 33.89\, b_{2,0}. \tag{8.2}$$

Given this expression for t = 0, the costs of biodiversity provision for each class in any other year t can be calculated as follows:

$$\psi_{1,t}(b_{1,t}) = \alpha_t\ \psi_{1,0}(b_{1,t}) = \alpha_t\ \left[0.54\ b_{1,t}^2 + 0.45\ b_{1,t}\right] \tag{9.1}$$

$$\psi_{2,t}(b_{2,t}) = \alpha_t\ \psi_{2,0}(b_{2,t}) = \alpha_t\ \left[2.08\ b_{2,t}^2 + 33.89\ b_{2,t}\right] \tag{9.2}$$

where α_t is the inflation rate for agricultural costs for year t, based on the 5-year average rate of increase in the prices paid by Spanish farmers (r_α), which is estimated at 2.17% according to official statistics:

$$\alpha_t = (1 + r_\alpha)^t = (1 + 0.0217)^t. \tag{10}$$

Note that the application of this inflation rate does not involve any assumption about future variations in provision costs; this is only used to calculate their future values assuming costs will remain the same in constant terms.

Table 2

Costs of biodiversity provision for each class of mountain olive farmers according to the AES scenarios considered

AES scenario	Increase in bird species/farm (no.)	Class 1 WTA or $\psi_{1,0}(b_{1,0})$ (€/ha/year)	Class 2 WTA or $\psi_{2,0}(b_{2,0})$ (€/ha/year)
Minimum level required (cross-compliance)	0.0	0.0	0.0
Integrated production	5.2	24.0	229.4
Integrated production plus	9.8	50.2	470.0
Ecological production	12.0	69.8	721.6
Ecological production plus	15.8	160.7	1,113.7
Provision of environmental public goods	22.2	273.0	1,756.0

Source: Authors' calculations from Villanueva *et al.* (2017c).

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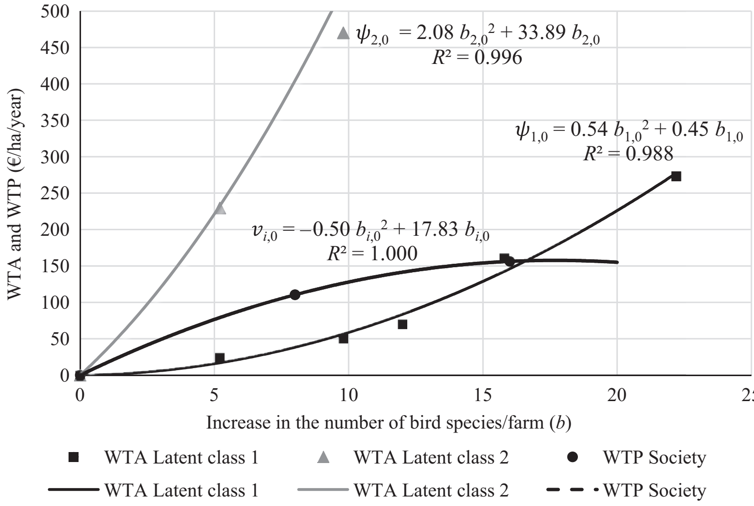

Figure 1. Cost of provision ($\psi_{i,0}(b_{i,0})$) and social benefit ($v_{i,0}(b_{i,0})$) (WTA and WTP, respectively) associated with biodiversity in MOG
Source: Authors' calculations using results of Villanueva *et al*. (2017c).

Finally, it is worth remarking that the administration managing the proposed AES has information about farmers' provision costs, since it knows the yields they obtain. Thus, our empirical application assumes that the regulator can detect the class of any farm willing to take part in the scheme. This means that the PAM framework proposed focuses only on the problem of moral hazard.

4.2. The social benefit from the improvement in the provision of biodiversity

The functional form $v_t(b_{it})$ was also obtained from the results of a valuation exercise carried out as part of the PROVIDE project (Villanueva *et al*., 2017c), the objective of which was to assess the Andalusian society's demand for public goods supplied by MOG. This valuation was carried out using choice experiments, by means of a random parameter logit (RPL) model using a dataset of a representative sample of 504 residents of the region.

The valuation of the demand for public goods determined the individual willingness to pay (WTP) for the improvement in the overall biodiversity in Andalusian MOG, measured for two separate levels: (i) a 'moderate' improvement, which means increasing the biodiversity to 22 bird species/farm; and (ii) a 'significant' improvement, equivalent to raising biodiversity levels to 30 bird species/farm. Moreover, it is assumed that the increase in the number of bird species is valued regardless of the farm type (class) providing this public good; that is, $v_{1,t}(b_{1,t}) = v_{2,t}(b_{2,t}) = v_t(b_{it})$.

These WTPs at the beginning of the contract period ($t = 0$) were quantified in euros/individual/year, as shown in the third column of Table 3. However, the units of measurement of the social benefit from the improvement in biodiversity need to be adapted to the proposed modelling exercise, in which WTP values are expressed in euros/hectare/year. To do so, the WTP values initially obtained from the valuation exercise should be multiplied by the number of individuals comprising the total population (6.72 million Andalusians over the age of 18 years) and divided by the total

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Table 3

Willingness to pay (WTP) for the improvement in biodiversity provision by MOG

AES Scenario	Increase bird species/farm (no.)	WTP (€/individual/year)	$v_0(b_0)$ (€/ha/year)
Reference level	0.0	0.00	0.00
Moderate improvement	8.0	3.46	110.38
Substantial improvement	16.0	4.90	156.26

Source: Authors' calculations from Villanueva *et al.* (2017c).

area of the analysed agricultural system (211,000 hectares)[5]; the results can be seen in the last column of Table 3.

Taking the WTP measured in euros/hectare/year, it is possible to estimate the functional form of v_0 by running the corresponding quadratic function regression, as shown in Figure 1. Thus, the function of the social benefit to be used in the optimisation model is as follows:

$$v_0\left(b_{i,0}\right) = -0.50\ b_{i,0}{}^2 + 17.83\ b_{i,0}. \tag{11}$$

As for the cost of provision, the values of social benefits for any other year t can be calculated as follows:

$$v_t\left(b_{i,t}\right) = \beta_t\ v_0\left(b_{i,t}\right) = \beta_t\ \left[-0.50\ b_{i,t}{}^2 + 17.83\ b_{i,t}\right] \tag{12}$$

where β_t in this case is the 5-year average of the general inflation rate in Spain (r_β), which is estimated at 0.84% according to official statistics:

$$\beta_t = \left(1 + r_\beta\right)^t = (1 + 0.0084)^t. \tag{13}$$

As pointed out for the provision cost, the application of this inflation rate is only used to calculate the future values of benefits assuming that they will remain the same in constant terms.

4.3. Other parameters of the model

The discount factor δ_t used to calculate present values is computed using the rate of the Spanish Treasury's 5-year bonds (r_δ = 0.40%), as follows:

$$\delta_t = \frac{1}{(1 + r_\delta)^t} = \frac{1}{(1 + 0.0040)^t}. \tag{14}$$

Based on Moschini and Hennessy (2002), we assume farmers' attitude to risk can be modelled by a CRRA (constant relative risk aversion) utility function with the following form[6]:

[5]This implicitly assumes that improvements in the number of bird species are evenly distributed among all MOG farms. An analysis explicitly accounting for spatial heterogeneity of improvements and benefits is beyond the scope of this study, but it would be worth examining in further research.

[6]This approach has been also followed by most of the previous literature in this field (e.g. Ozanne *et al.*, 2001; Fraser, 2002, 2004, 2012; Bontems and Thomas, 2006; Ozanne and White, 2008).

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$$U(\pi_i) = \frac{\pi_i^{1-R_i}}{1 - R_i} \tag{15}$$

where R_i is the Arrow-Pratt (positive and constant) coefficient of relative risk aversion for farmer i, representing the elasticity of the marginal utility function:

$$R_i = -\frac{\pi_i \; U''(\pi_i)}{U'(\pi_i)}. \tag{16}$$

Moreover, the model presented above is based on the assumption that the principal knows the producers' attitude to risk (value of R_i). While risk preferences can vary significantly across farmers,[7] the empirical evidence indicates that the relative risk aversion coefficient typically varies between 0.5 (slightly risk-averse) and 4 (extremely risk-averse) (Gollier, 2004, p. 31). On this basis, we assume a moderate level of risk aversion of 2 (Chavas and Di Falco, 2012) for the two farmer types considered ($R_1 = R_2 = R = 2$).

We consulted a panel of technicians from the administration and agricultural organisations with experience in AES inspections about the probability of detecting non-compliance with the scheme ($\theta(c_{it})$). This panel generally agreed that a realistic functional form would be a sigmoid type (see black line in Figure 2), rather than the linear function used in most previous applications (see grey line in Figure 2). To determine the specific form of this function, panel members were asked to provide subjective probabilities of $\theta(c_{it})$ for different levels of compliance. Thus, from the pairs of values $[\theta(c_{it}),\ c_{it}]$, the functional form has been determined that best fits the cloud of points obtained. This function is the Boltzmann sigmoid function, defined as follows:

$$\theta(c_{it}) = \frac{A_1 - A_2}{1 + e^{(c_{it}-\alpha)/\beta}} + A_2 = 1 - \frac{1}{1 + e^{\frac{0.7-c_{it}}{0.05}}}. \tag{17}$$

The most reliable estimation of the MCF (λ) is the one provided by Kleven and Kreiner (2006), who calculated the MCF for a proportional tax rate increase (an equal marginal tax rate increase in all tax brackets) in several OECD countries. The MCF they computed ranged from 1.29 in Denmark to 1.10 in the United Kingdom, under reasonable assumptions regarding labour supply elasticities (Dahlby, 2008, p. 129). Given the divergence in these estimates, we opted to solve the principal's decision problem by using an intermediate value for λ, equal to 1.2.

Under European legislation, Member States can impose sanctions based on a variable reduction in the amount of the payment received each year. This means that $\rho(c_{it})$ can take different values within the interval [0,1]. Taking into account a standard implementation of sanction systems, we assume that sanctions follow a linear function dependent on the degree of compliance:

$$\rho(c_{it}) = 1 - c_{it}. \tag{18}$$

Given the lack of information on monitoring costs (Mettepenningen *et al.*, 2011), it is impossible to estimate the functional form, so we assume a linear monitoring cost:

[7] Gómez-Limón *et al.* (2003) and Orea and Wall (2012) have analysed variability in risk-aversion among Spanish farmers. Both studies provide evidence that the coefficient of relative risk aversion ranges between 0 and more than 25, with a mean estimate around 3.

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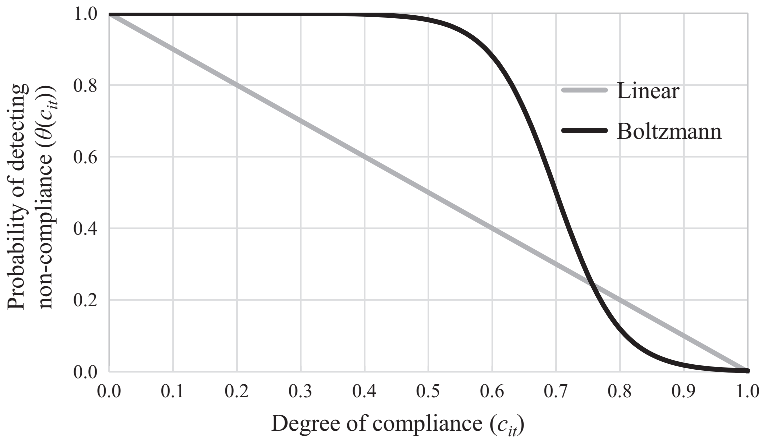

Figure 2. Functional form of the probability of detecting non-compliance ($\theta(c_{it})$)
Source: Authors' calculations.

$$M(m_{it}) = m_i k \tag{19}$$

where k is the cost of monitoring per hectare subject to control.

The value of k was estimated based on the information provided by the Andalusian public agency that carries out these inspections. According to the data provided, in 2015, 1,006 of the 12,867 AES files in Andalusia were checked (representing 7.8% of the total, notably higher than the 5% minimum required by EU legislation). To carry out these inspections, 36 technicians had to be hired for a total of 22,278 working days, representing an average of 22.15 working days per file. As a result, the approximate cost per file is estimated at €2,800. Taking into account the fact that the average file for these schemes in Andalusia covers 26 hectares, the cost per monitored hectare is €108 (k = €108/ha).

4.4. Base scenario and sensitivity analysis

Our PAM for optimal AES design is calibrated with these best available parameter value estimates to represent the 'base scenario'. However, most of these estimates are subject to some degree of uncertainty. To address this concern, we use a sensitivity analysis to identify which parameter estimates could critically impact model results (optimal AES design). The analysis is focused on the following five key parameters (those subject to greater uncertainty in their estimation):

1 cost of provision of biodiversity, $\psi_{it}\left(b_{i,t}\right)$;
2 coefficient of relative risk aversion for farmers, R;
3 social benefit from the improvement in the provision of biodiversity, $v_t\left(b_{i,t}\right)$;
4 marginal cost of public funds, λ;
5 monitoring costs, k.

Thus, after obtaining the results for the base scenario (see section 5), the PAM was run a number of additional times, using +10% and −10% changes (*ceteris paribus*) in the values of each key parameter. The results obtained by following this procedure

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are reported in section 6.1 and provide information on which parameters would be worthy of more accurate estimation.

5. Results: Optimal AES Design for the Base Scenario

As shown in Figure 1, the high WTA in Class 2 means that this group's costs to increase biodiversity provision ($\psi_{2,t}(b_{2,t})$) exceed the associated social benefit ($v_t(b_{2,t})$) for any level of improvement in this public good and any year ($b_{2,t}$). Hence, when social welfare is maximised (optimal solution running model (expression 7)),[8] this class does not satisfy the participation constraint (expression (7.2)), meaning that the proposed optimisation model excludes it from implementation of the scheme ($\gamma_2 = 0$). Thus, all the principal's decision variables regarding this class (B_2, p_2 and m_2) also take null values.

This first result is relevant because Class 2 includes 40.5% of the olive farms analysed, and their non-participation in the proposed AES limits the potential of this instrument to improve social welfare. However, it is worth remarking that gaps between the cost of provision of public goods and the associated social benefit are common in real-world situations (not all underprovision situations can be considered market failures), with one or several groups of farmers deterred from signing up to AES contracts. In fact, there is evidence that most AES are targeted at a relatively wide range of farmers, but only a certain share of them – those with lower compliance costs (in our case study, those with farms with lower yields, i.e. lower income foregone) – take part in the scheme (Quillérou *et al.*, 2011).

On the other hand, there is an upside to this situation in terms of the practical implementation of the proposed scheme, in that it simplifies the management and reduces potential problems of adverse selection. Indeed, although the application of the proposed AES assumes that the regulator can detect whether farms belong to Class 1 or 2 (there is no adverse selection problem), this assumption could be relaxed for the specific case study analysed, since the participation constraint enables farm types to be distinguished from one another, even in case of hidden information.

In light of this result, the optimal AES design would be based on a single agri-environmental contract designed for farms with the lowest costs of provision (Class 1). Accordingly, AES could be uniformly rolled out through a single contract applicable to all olive groves, which would reduce the transaction costs of the scheme for both the public administration and the farmers, by facilitating the promotion of the scheme, information and support provided, contracting and subsequent evaluation.

The optimal values for the principal's decision variables (B_1, p_1 and m_1) and the objective function (Z) resulting from the model (expression (7)) for the base scenario are shown in Table 4. The maximum increase in social welfare for this scenario is €129.66 for the whole contract period per enrolled hectare. Thus, considering that all farms included in Class 1 (125.545 ha) would participate in the proposed scheme,

[8]It is worth remarking that, since AES are voluntary contracts, the enrolment of Class 2 in the proposed scheme could only be achieved by setting extremely high payments (p_2) covering compliance costs ($\psi_{2t}(b_{2t})$) for any effective improvement in the provision of biodiversity (b_{2t}). Thus, taking into account the fact that this cost of provision is much higher than the associated social benefit, the option of promoting Class 2 engagement in this scheme would lead to a decrease in social welfare (inefficient policy implementation).

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Table 4

Optimal AES design for the base scenario

MOG farm type 1 ($\gamma_1 = 1$)		MOG farm type 2 ($\gamma_2 = 0$)		All MOG farms	
Z_1 (M€/MOG/5-year)*	16.3	Z_2 (M€/MOG/5-year)*	0.0	Z (M€/MOG/5-year)*	16.3
P_1 (M€/MOG/5-year)*	56.3	P_2 (M€/MOG/5-year)*	0.0	P (M€/MOG/5-year)*	56.3

$t(b_{1t}$	$t = 1$	$t = 2$	$t = 3$	$t = 4$	$t = 5$	Average*
z_{1t} (€/ha/year)	26.2	26.3	26.3	26.3	26.0	25.9
p_{1t} (€/ha/year)	90.7	90.7	90.7	90.7	90.7	89.7
B_{1t} (no. species/farm)	7.6	7.6	7.6	7.6	7.6	7.6
m_{1t} (%)	0.14	0.14	0.14	0.14	0.14	0.14
c_{1t} (%)	0.68	0.67	0.67	0.66	0.65	0.67
b_{1t} (no. species/farm)	5.2	5.1	5.1	5.1	4.9	5.1
$\psi_{1t}(b_{1t})$ (€/ha/year)	17.1	17.2	17.3	17.3	17.1	17.0
π_{1t} (€/ha/year)	71.1	70.9	70.6	70.4	70.3	69.8
$v_t(b_{1t})$ (€/ha/year)	79.1	79.3	79.39	79.3	78.8	78.2

Notes: *Average and aggregated monetary terms are measured in constant euros at year $t = 0$.
Source: Authors' calculations.

social welfare would be improved by €16.28 million over the 5-year implementation period. To achieve this enhanced welfare, the proposed AES should commit mountain olive growers to implementing agri-environmental practices that increase the provision of biodiversity by a measure of 7.62 bird species/farm, in exchange for a payment of €90.73/hectare/year (totalling €11.39 million a year for the total MOG area included in Class 1).

This base scenario also involves an optimal monitoring level of 14.0%, which is significantly higher than the 5% minimum required by EU legislation, and also higher than the 7.8% current practice in the region.

As defined for modelling purposes, the results of the variables describing farmers' behaviour depend on the year within the contract period (see Table 4). However, since it has been assumed that all policy variables set by the principal (required increase in the provision of biodiversity, B_1; agri-environmental payments, p_1; percentage levels of monitoring, m_1; and sanctions, $\rho(c_{it})$) remain constant throughout the whole contract period, and that the estimated values of provision costs ($\psi_{1t}(b_{1t})$) and social benefits ($v_t(b_{1t})$) also remain the same in constant terms, optimal values of these variables describing agent's behaviour are quite stable over the 5-year period. In fact, the slight changes in farmers' behaviour (c_{1t}) during the contract period are negligible adjustments caused by the small difference between the inflation rate for provision costs ($r_\alpha = 2.17\%$) and social benefits ($r_\beta = 0.84\%$). In light of this circumstance, we recommend taking the average optimal values for the whole period.

The optimal AES design, as indicated above, means that the Class 1 farms sign up to the scheme ($\gamma_1 = 1$) with the agents choosing a degree of compliance with the agri-environmental requirements of around 67.0% (i.e. the effective increase in the number of bird species per farm would be about 5.05). This partial compliance with the scheme entails an average extra expected cost of only €16.98/ha/year (totalling €23.08 million/year for all farms involved), such that signing up to this instrument provides the agents with an extra expected profit of €69.82/ha/year (a total of €43.83 million/

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year for all farms involved). Society, on the other hand, benefits to the amount of €78.24/ha for the effective increase in the provision of biodiversity (equivalent to a total of €49.83 million).

Although the results of the PAM for the base scenario reveal the proposed AES to be an effective way of improving the social welfare associated with the provision of biodiversity by MOG, it can be noted that the welfare gain generated is limited compared to the amount of the public budget dedicated to that aim. Indeed, for every €100 of public spending invested in the scheme, a net welfare improvement of only €28.93 would be obtained. It is also striking that, for every €100 that the farmers receive as agri-environmental payments, only €18.94 goes towards covering the expected costs incurred to improve biodiversity, while €77.88 is converted into an increase in their expected private profit (the remaining €3.18 is lost due to the inefficiencies of policy implementation).

6. Discussion

6.1. Sensitivity analysis

Table 5 summarises the results obtained from the sensitivity analysis. These results show that value deviations (estimation errors) in the parameter λ (the marginal cost of public funds, MCF) has the most critical impact on the optimal results derived from the model (expression 7). A 10% increase in this parameter leads to a significant reduction in the effectiveness of this policy instrument, with a 40% lower improvement in social welfare than in the base scenario. This is because a more inefficient tax system involves a higher social cost of public spending policies, resulting in lower optimal values for policy objectives (B_1 decreases by 20%) and agri-environmental payments (p_1 declines by 33%). A 10% decrease in this parameter generates opposite impacts that are even more significant: an increase in the improvement of social welfare (60%), biodiversity enhancement (24%) and agri-environmental payments (85%).

The need for accurate estimates of social benefits of public goods is also worth highlighting since demand-side valuation assessments are seldom implemented by official institutions to support policy-making. Most of these valuation exercises are carried out by academics focused on scientific issues, and cannot easily be used to feed the PAM. Therefore, the availability of robust parameters to estimate social benefit is another limitation for policy analysts when modelling this kind of instrument.

Parameters used to estimate the cost of provision ($\psi_{it}(b_{i,t})$) are also relevant, although to a lesser extent. An increase (decrease) in the cost estimate would lead a 12% decrease (14% increase) in optimal social welfare. However, the rest of the policy-making variables would change by less than 10%.

Changes in the parameters regarding the coefficient of relative risk aversion for farmers (R) and monitoring costs (k) have moderate to light impacts on optimal results. With regards to the former, variations in all policy-making variables shown in Table 5 are lower than 5% for scenarios of $\pm10\%$ change in R. This suggests that assumptions about farmers' risk aversion may not have as great an effect as was found in previous theoretical works by Ozanne *et al.* (2001) and Fraser (2004). Concerning the parameter k, as with the parameter R, the accuracy in its estimation is not such a determining factor as for those mentioned above. Of the five parameters analysed, this is the only one that can be set by the principal; indeed, minimising monitoring costs is

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Table 5

Optimal AES design and sensitivity analysis (percentage variations compared with the base scenario shown in parentheses)

	Base scenario	$\psi_{it}(b_{i,t})$		$v_t(b_{i,t})$		R		λ		k	
		+10%	−10%	+10%	−10%	+10%	−10%	+10%	−10%	+10%	−10%
Z_1 (€/ha/5-year)	129.7	113.7 (−12.3%)	148.1 (+14.3%)	170.5 (+31.5%)	92.6 (−28.5%)	135.5 (+4.5%)	124.0 (−4.4%)	78.4 (−39.5%)	207.1 (+59.8%)	121.0 (−6.6%)	139.0 (+7.2%)
p_1 (€/ha/year)	90.7	87.5 (−3.6%)	93.9 (+3.5%)	100.8 (+11.1%)	79.7 (−12.1%)	89.3 (−1.5%)	92.0 (+1.4%)	60.8 (−33.0%)	167.9 (+85.0%)	92.3 (+1.8%)	88.8 (−2.2%)
B_1 (no. species/farm)	7.6	7.0 (−8.2%)	8.3 (+9.3%)	8.5 (+11.1%)	6.7 (−12.3%)	7.8 (+2.3%)	7.4 (−2.3%)	6.1 (−19.6%)	9.5 (+24.2%)	7.4 (−3.0%)	7.8 (+3.1%)
m_1 (%)	0.14	0.14 (−3.4%)	0.14 (+3.3%)	0.16 (+10.7%)	0.12 (−11.9%)	0.14 (−1.4%)	0.14 (+1.2%)	0.14 (−2.1%)	0.12 (−17.9%)	0.13 (−7.4%)	0.15 (+8.5%)
Average c_{1t} (%)	0.67	0.67 (+0.0%)	0.67 (+0.0%)	0.67 (+0.1%)	0.67 (−0.1%)	0.67 (−0.3%)	0.67 (+0.3%)	0.67 (+0.0%)	0.67 (−0.2%)	0.67 (−0.1%)	0.67 (+0.1%)
Average b_{1t} (no. species/farm)	5.1	4.6 (−8.2%)	5.5 (+9.3%)	5.6 (+11.3%)	4.4 (−12.5%)	5.2 (+2.0%)	5.0 (−2.0%)	4.1 (−19.6%)	6.3 (+23.9%)	4.9 (−3.0%)	5.2 (+3.2%)
Average $\psi_{1t}(b_{1t})$ (€/ha/year)	17.0	15.9 (−6.2%)	18.0 (+6.2%)	20.7 (+22.1%)	13.3 (−21.8%)	17.6 (+3.7%)	16.4 (−3.6%)	11.3 (−33.2%)	25.4 (+49.5%)	16.0 (−5.6%)	18.0 (+6.0%)
Average π_{1t} (€/ha/year)	69.8	67.9 (−2.8%)	71.7 (+2.7%)	75.4 (+7.9%)	63.3 (−9.3%)	67.8 (−2.8%)	71.7 (+2.6%)	46.9 (−32.9%)	136.2 (+95.1%)	72.5 (+3.9%)	66.7 (−4.5%)
Average $v_t(b_{1t})$ (€/ha/year)	78.2	72.8 (−7.0%)	84.2 (+7.6%)	94.0 (+20.1%)	62.9 (−19.6%)	79.5 (+1.6%)	77.0 (−1.6%)	64.9 (−17.0%)	93.1 (+19.0%)	76.2 (−2.5%)	80.3 (+2.6%)

Source: Authors' calculations.

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a particularly accessible way of increasing the efficiency of AES. However, in line with previous studies (a recent literature review can be found in Shimshack, 2014), our results raise some doubts about the cost-effectiveness of current environmental monitoring practices.

Finally, although the changes in the key parameters analysed generate notable changes in the optimal values of the principal's decision variables, the same cannot be said for the agent's decision variable (level of compliance, c_{1t}). Indeed, the optimal value of this variable remains fairly stable at around 67%, with changes no greater than 0.5% for 10% variations in the parameters. This is a result of the first-order condition of the agent optimisation problem and, more specifically, the function of the probability of detecting non-compliance with the scheme ($\theta(c_{it})$), leading to optimal solutions located around the inflexion point ($c_{it} = 0.7$ as estimated for our case study).

6.2. Sanctions for non-compliance

As indicated above regarding the results of base scenario, the contribution of the proposed AES to enhancing social welfare is rather disappointing, since only 19% of the agri-environmental payments received by farmers is used to compensate for the extra expected cost stemming from the required environmentally-friendly practices, and almost all the rest is converted into extra expected private profit. This situation is a direct consequence of the information asymmetry inherent in the implementation of AES. Thus, the resulting solutions of the proposed optimisation model are second-best solutions, and are a long way from the optimal solution that would be attainable if there were perfect information. Previous research such as that of Ozanne and White (2008) has pointed out that AES performance could be improved by imposing a tougher system of sanctions for non-compliance. Such a system would not only proportionally reduce agri-environmental payments on the basis of the degree of non-compliance, as per current practice, but in cases of serious non-compliance, as well as completely stopping all payments, farmers could be fined (that is, $\rho(c_i)$ could be greater than one).

In order to explore this possibility, alternative sanction systems increasing the sanction share have been simulated following this general expression:

$$'\text{Sanction } + \text{ AS}' \text{ system: } \rho_S(c_{it}) = (1 + AS) \cdot (1 - c_{it}). \tag{20}$$

This expression means that if non-compliance were detected, farmers would be sanctioned with a proportional reduction in the agri-environmental payment granted plus an additional sanction share equal to AS, measured as a percentage of the payment. Thus, in the model (expression (7)) $\rho(c_{it})$ (expression (18)) has been replaced by $\rho_S(c_{it})$ (expression (20)), and the resulting model has been run several times parameterising the AS. The results obtained for AS = 10%, AS = 20%, and AS = 28% can be seen in Table 6.

There is an overall improvement in the efficiency of the scheme as a result of these alternative sanction systems compared to the base scenario. Thus, the social welfare gain increases as the value of S grows, until the implementation of the 'Sanction +28%' system, which would result in a welfare increase of €199.29/hectare for the whole contract period (equivalent to €25.02 million in total), representing a 53.7% higher welfare compared to the base scenario. No further rise in social welfare is possible by increasing the value of the parameter S, since the model (expression (7))

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Table 6

Optimal AES design for the different sanction systems

	Base scenario	'Sanction +10%' system	'Sanction +20%' system	'Sanction +28%' system
Z_1 (€/ha/5-year)	129.7	148.0 (+14.1%)	169.3 (+30.6%)	199.3 (+53.7%)
p_1 (€/ha/year)	90.7	85.3 (–6.0%)	74.4 (–18.0%)	59.3 (–34.6%)
B_1 (no. species/farm)	7.6	8.2 (+8.3%)	9.1 (+20.0%)	9.6 (+26.4%)
m_1 (%)	0.14	0.14 (–1.4%)	0.14 (+2.0%)	0.13 (–6.2%)
Average c_{1t} (%)	0.67	0.66 (–0.8%)	0.65 (−2.1%)	0.66 (–0.6%)
Average b_{1t} (no. species/farm)	5.1	5.4 (+7.4%)	5.9 (+17.5%)	6.4 (+25.7%)
Average $\psi_{1t}(b_{1t})$ (€/ha/year)	17.0	19.4 (+14.2%)	23.0 (+35.2%)	26.1 (+53.5%)
Average π_{1t} (€/ha/year)	69.8	62.1 (–11.1%)	47.8 (–31.5%)	32.5 (–53.5%)
Average $v_t(b_{1t})$ (€/ha/year)	78.2	83.0 (+6.0%)	89.2 (+14.1%)	94.1 (+20.3%)

Source: Authors' calculations.

cannot find a better solution for the objective function than the one obtained for $S = 28\%$.

Regarding the optimal solution for the base scenario, the design of the scheme incorporating alternative sanction systems results in a significant increase in the level of environmental stringency (up to +26.4% for 'Sanction +28%' system). The same cannot be said, however, of payments associated with the AES. In fact, the optimal amounts of the agri-environmental payments with these alternative sanction systems would be lower than those in the current scenario, thus requiring a smaller budgetary allocation for the implementation of the scheme. For the toughest sanctions system considered, these payments would be 34.6% lower than those calculated for base scenario.

These changes in the principal's decision variables lead to a significant improvement in the provision of biodiversity by MOG. In particular, as shown in Table 6, as the sanctions increase, the effective environmental performance (average b_{1t}) increases from 5.05 bird species per farm in the base scenario to 6.35 bird species in the 'Sanction +28%' system scenario (+25.7%), with the other two tougher sanction scenarios also showing notable increases compared to the base scenario. This is explained by the increase in the targeted improvement in environmental performance (B_1, from +8.3% to +26.4%, depending on the sanction system considered), coupled with a fairly stable level of compliance showing only small decreases (from –0.6% to –2.1%, depending on the sanction system).

It is also notable that the alternative sanction systems proposed can reduce the overcompensation of farmers stemming from information asymmetry. In fact, the

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percentage of the payment used to cover the costs incurred for improving biodiversity increases from 19%, as reported above for the base scenario, to 23% for the 'Sanction +10%' system, 31% for the 'Sanction +20%' system, and up to 45% for 'Sanction +28%' system.

Finally, it should be noted that with the alternative sanction systems, the optimal monitoring level is slightly reduced in comparison to the base scenario. In any case, it should be borne in mind that with these sanction systems the optimal monitoring values are above 10% in all cases. Again, this demonstrates that it is appropriate to raise the current monitoring levels for AES.

6.3. Dynamic detection of non-compliance

We have followed current common implementation practices in the EU by holding agri-environmental payments, percentage levels of monitoring and sanctions constant throughout the whole contract period. However, the multiple-period PAM is capable of exploring the dynamics of the delivery of public goods over time, for instance: (i) changes in real terms in both the costs of provision and the social benefits from public goods; (ii) the existence of initial investment costs to implement the required agri-environmental practices; or (iii) changes in the likelihood of detection of non-compliance.

In particular, our panel of technicians suggested that the likelihood of detection of non-compliance usually increases over the contract period, so we also considered interannual changes in the probability function of detecting non-compliance with the scheme. This application (detailed in the online Appendix) illustrates how the multiple-period PAM approach developed can capture the dynamic of AES, showing how a more accurate detection of non-compliance leads to an improvement in social welfare Z (+4.4%) compared to the base scenario. This improvement is explained by the decrease in agri-environmental payment p_1 (–2.7%) and the increase in the environmental performance B_1 (+4.7% on average for the whole contract period), with the latter mainly caused by an increase in famers' compliance c_{1t} (+5.5% on average).

7. Conclusions

We demonstrate the use of a principal-agent model (PAM) to support the design of an agri-environment scheme (AES), to minimise moral hazard, using best estimates of the major parameters, and exploring the sensitivity of the design to these parameters. We identify and include the substantial amount of information needed to create realistic and practically useful applications. In particular, we employ choice experiment estimates of the farmers' costs of implementation (the willingness to accept – WTA – AES contracts), and of the social value of the improved biodiversity (the willingness to pay – WTP – for measured bird richness).

Our application shows that the second-best solutions yielded by the PAM can differ significantly from the optimal achievable in an ideal world of perfect information. Our optimal solutions reveal that only a small part of the agri-environment payments goes towards compensating farmers for the extra costs incurred as a result of implementing the AES; most of this payment is converted to farmers' expected private profit. Our results suggest the importance of moderating payments depending on the farmers' degree of compliance, and of penalising non-compliance by imposing fines in

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cases of serious breaches. They also suggest that the current level of monitoring of AES should be increased.

We identify that the parameter which has the most critical influence on the optimal AES design is the marginal cost of public funds, as a measure of the efficiency of the tax system. Other key parameters determining PAM results are those used to estimate farmers' cost of provision of the public good and the social benefit associated with this improvement.

Despite the attempt to take a realistic approach to developing this model to support the design of the proposed AES, a number of limitations can be identified clearly representing issues for further research. Some of these have already been addressed in the literature from a theoretical point of view, such as the omission of transaction costs other than monitoring costs (Mettepenningen *et al*., 2011), or the assumption of an equal utility function and risk aversion coefficient for all farmers (Gómez-Limón *et al*., 2003; Orea and Wall, 2012). Similarly, although our empirical application accounts for alternative AES designs with increasing probability of detection of non-compliance, it does not do so for inter-temporal variation of payments, monitoring level and sanctions throughout the contract period. As shown by Fraser (2012), this would provide a broader picture of farmers' behaviour that could be useful when incorporating time issues to ensure more efficient scheme design. Additionally, with respect to monitoring, it would be appropriate to analyse the implementation of non-random monitoring strategies; for example, focusing controls on those farmers with higher risks of non-compliance and/or a history of previous breaches (Fraser, 2004). These issues can be further explored using the PAM approach.

There are other aspects that have not yet been addressed in the literature but that should be examined in future empirical studies regarding optimal design of AES using PAM. For instance, it would be of special interest to incorporate spatial analysis into this modelling approach, particularly to take into account spatial features (biophysical conditions, proximity to natural areas, etc.) and collective rather than individual participation (i.e. neighbouring effects on the provision of farmland biodiversity and the role of the agglomeration bonus) as key factors determining biodiversity performance. In addition, the use of the Cumulative Prospect Theory (CPT) could be explored as an alternative to the Expected Utility Theory (EUT). Recent studies (e.g. Bocquého *et al*., 2014) provide evidence that farmers are more sensitive to losses (i.e. AES sanctions for cheating) than to gains (i.e. AES payments for enrolment). Consequently, accounting for loss aversion and probability weighting can make a difference in the design of effective and efficient contract schemes. Furthermore, we could also consider evidence that farmers' conservation behaviour is driven by various motivations and criteria related to their economic, social, cultural, and natural environment situation, in addition to the expected utility of profit (Lastra-Bravo *et al*., 2015). This fact suggests that testing new PAM approaches based on the Multi-Attribute Utility Theory (MAUT) or the Theory of Planned Behaviour (TPB) would provide new insights into the analysis of conservation-oriented attitudes and other personal motivations for AES participation and compliance.

Supporting Information

Additional Supporting Information may be found in the online version of this article:

Dynamic detection of non-compliance

Table S1. Optimal AES design for the dynamic scenario.

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References

Auerbach, A. J. and Hines, J. R. 'Taxation and economic efficiency', in: A. J. Auerbach and M. Feldstein (eds.), *Handbook of Public Economics* (Amsterdam: Elsevier, 2002, pp. 1347–1421).

Bartolini, F., Gallerani, V., Raggi, M. and Viaggi, D. 'Modelling the linkages between cross-compliance and agri-environmental schemes under asymmetric information', *Journal of Agricultural Economics*, Vol. 63, (2012) pp. 310–330.

Blandford, D. 'Information deficiencies in agricultural policy design, implementation and monitoring', *OECD Food, Agriculture and Fisheries Working Papers*, Vol. 6, (2007) pp. 1–58.

Bocquého, G., Jacquet, F. and Reynaud, A. 'Expected utility or prospect theory maximisers? Assessing farmers' risk behaviour from field-experiment data', *European Review of Agricultural Economics*, Vol. 41, (2014) pp. 135–172.

Bontems, P. and Thomas, A. 'Regulating nitrogen pollution with risk averse farmers under hidden information and moral hazard', *American Journal of Agricultural Economics*, Vol. 88, (2006) pp. 57–72.

Carmona-Torres, C., Parra-López, C., Sayadi, S. and Chirosa-Ríos, M. 'A public/private benefits framework for the design of polices oriented to sustainability in agriculture: An application to olive growing', *Land Use Policy*, Vol. 58, (2016) pp. 54–69.

Chavas, J.-P. and Di Falco, S. 'On the role of risk versus economies of scope in farm diversification with an application to Ethiopian farms', *Journal of Agricultural Economics*, Vol. 63, (2012) pp. 25–55.

Choe, C. and Fraser, I. 'Compliance monitoring and agri-environmental policy', *Journal of Agricultural Economics*, Vol. 50, (1999) pp. 468–487.

Dahlby, B. *The Marginal Cost of Public Funds: Theory and Applications* (Cambridge, USA: MIT University Press, 2008).

Duarte, J., Campos, M., Guzmán, J. R., Beaufoy, G., Farfán, M. A., Cotes, B., Benítez, E., Vargas, J. M. and Muñoz-Cobo, J. 'Olivar y biodiversidad', in J. A. Gómez Calero (ed.), *Sostenibilidad de la producción de olivar en Andalucía* (Sevilla: Consejería de Agricultura y Pesca, Junta de Andalucía, 2009, pp. 162–222).

EEA (European Environmental Agency). *Assessing Biodiversity in Europe – The 2010 Report*. EEA Report No 5/2010 (Copenhagen: European Environmental Agency, 2010).

Fraser, R. 'Moral hazard and risk management in agri-environmental policy', *Journal of Agricultural Economics*, Vol. 53, (2002) pp. 475–487.

Fraser, R. 'On the use of targeting to reduce moral hazard in agri-environmental schemes', *Journal of Agricultural Economics*, Vol. 55, (2004) pp. 525–540.

Fraser, R. 'Moral hazard, targeting and contract duration in agri-environmental policy', *Journal of Agricultural Economics*, Vol. 63, (2012) pp. 56–64.

Fraser, R. 'To cheat or not to cheat: Moral hazard and agri-environmental policy', *Journal of Agricultural Economics*, Vol. 64, (2013) pp. 527–536.

Fraser, R. *Applications of Principal-Agent Theory to Agricultural Land Use Policy: Lessons from the European Union* (London: Imperial College Press, 2015).

Gollier, C. *The Economics of Risk and Time* (Boston, MA: The MIT Press, 2004).

Gómez-Limón, J. A., Arriaza, M. and Riesgo, L. 'An MCDM analysis of agricultural risk aversion', *European Journal of Operational Research*, Vol. 151, (2003) pp. 569–585.

Hart, R. and Latacz-Lohmann, U. 'Combating moral hazard in agri-environmental schemes: A multiple-agent approach', *European Review of Agricultural Economics*, Vol. 32, (2005) pp. 75–91.

Hart, K., Baldock, D., Weingarten, P., Osterburg, B., Povellato, A., Vanni, F., Pirzio-Biroli, C. and Boyes, A. *What Tools for the European Agricultural Policy to Encourage the Provision of Public Goods?* (Brussels: European Parliament, 2011).

Hess, S., Ben-Akiva, M., Gopinath, D. and Walker, J. *Advantages of Latent Class over Continuous Mixture of Logit Models (Institute for Transport Studies* (Leeds, UK: University of Leeds, 2011).

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Kleven, H. J. and Kreiner, C. T. 'The marginal cost of public funds: Hours of work versus labor force participation', *Journal of Public Economics*, Vol. 90, (2006) pp. 1955–1973.

Laffont, J.-J. and Martimort, D. *The Theory of Incentives: The Principal-agent Model* (Princeton, NJ: Princeton University Press, 2009).

Lastra-Bravo, X.B., Hubbard, C., Garrod, G. and Tolón-Becerra, A. 'What drives farmers' participation in EU agri-environmental schemes? Results from a qualitative meta-analysis', *Environmental Science & Policy*, Vol. 54(Supplement), (2015) 1–9.

Melkonyan, T. and Taylor, M. H. 'Regulatory policy design for agroecosystem management on public rangelands', *American Journal of Agricultural Economics*, Vol. 95, (2013) pp. 606–627.

Mettepenningen, E., Beckmann, V. and Eggers, J. 'Public transaction costs of agri-environmental schemes and their determinants. Analysing stakeholders' involvement and perceptions', *Ecological Economics*, Vol. 70, (2011) pp. 641–650.

Moschini, G. and Hennessy, D. A. 'Uncertainty, risk aversion, and risk management for agricultural producers', in B.L. Gardner and G.C. Rausser (eds.), *Handbook of Agricultural Economics* (Elsevier: Amsterdam, 2002, pp. 88–153).

Moxey, A., White, B. and Ozanne, A. 'Efficient contract design for agri-environment policy', *Journal of Agricultural Economics*, Vol. 50, (1999) pp. 187–202.

OECD (Organisation for Economic Co-operation and Development). *Guidelines for Cost-Effective Agri-Environmental Policy Measures* (Paris: OECD Publishing, 2010).

OECD (Organisation for Economic Co-operation and Development). *Public Goods and Externalities: Agri-Environmental Policy Measures in Selected OECD Countries* (Paris: OECD Publishing, 2015).

Orea, L. and Wall, A. 'Productivity and producer welfare in the presence of production risk', *Journal of Agricultural Economics*, Vol. 63, (2012) pp. 102–118.

Ozanne, A. and White, B. 'Hidden action, risk aversion and variable fines in agri-environmental schemes', *Australian Journal of Agricultural and Resource Economics*, Vol. 52, (2008) pp. 203–212.

Ozanne, A., Hogan, T. and Colman, D. 'Moral hazard, risk aversion and compliance monitoring in agri-environmental policy', *European Review of Agricultural Economics*, Vol. 28, (2001) pp. 329–348.

Paracchini, M.L., Petersen, J.-E., Hoogeveen, Y., Bamps, C., Burfield, I. and van Swaay, C. *High Nature Value Farmland in Europe. An Estimate of the Distribution Patterns on the Basis of Land Cover and Biodiversity Data* (Luxembourg: Office for Official Publications of the European Communities, 2008).

Quillérou, E. and Fraser, R. 'Adverse selection in the environmental stewardship scheme: Does the higher level stewardship scheme design reduce adverse selection?', *Journal of Agricultural Economics*, Vol. 61, (2010) pp. 369–380.

Quillérou, E., Fraser, R. and Fraser, I. 'Farmer compensation and its consequences for environmental benefit provision in the higher level stewardship scheme', *Journal of Agricultural Economics*, Vol. 62, (2011) pp. 330–339.

Rocamora-Montiel, B., Glenk, K. and Colombo, S. 'Territorial management contracts as a tool to enhance the sustainability of sloping and mountainous olive orchards: Evidence from a case study in Southern Spain', *Land Use Policy*, Vol. 41, (2014) pp. 313–325.

Rodríguez-Entrena, M., Espinosa-Goded, M. and Barreiro-Hurlé, J. 'The role of ancillary benefits on the value of agricultural soils carbon sequestration programmes: Evidence from a latent class approach to Andalusian olive groves', *Ecological Economics*, Vol. 99, (2014) pp. 63–73.

Shimshack, J. P. 'The economics of environmental monitoring and enforcement', *Annual Review of Resource Economics*, Vol. 6, (2014) pp. 339–360.

Stroosnijder, L., Mansinho, M. I. and Palese, A. M. 'OLIVERO: The project analysing the future of olive production systems on sloping land in the Mediterranean basin', *Journal of Environmental Management*, Vol. 89, (2008) pp. 75–85.

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Uthes, S. and Matzdorf, B. 'Studies on agri-environmental measures: A survey of the literature', *Environmental Management*, Vol. 51, (2013) pp. 251–266.

Viaggi, D., Bartolini, F. and Raggi, M. 'Combining linear programming and principal–agent models: An example from environmental regulation in agriculture', *Environmental Modelling and Software*, Vol. 24, (2009) pp. 703–710.

Villanueva, A. J., Gómez-Limón, J. A., Arriaza, M. and Rodríguez-Entrena, M. 'The design of agri-environmental schemes: Farmers' preferences in southern Spain', *Land Use Policy*, Vol. 46, (2015) pp. 142–154.

Villanueva, A. J., Gómez-Limón, J. A. and Rodríguez-Entrena, M. 'Valoración de la oferta de bienes públicos por parte de los sistemas agrarios: el caso del olivar de montaña en Andalucía', *Economía Agraria y Recursos Naturales*, Vol. 17, (2017a) pp. 25–58.

Villanueva, A. J., Rodríguez-Entrena, M., Arriaza, M. and Gómez-Limón, J. A. 'Heterogeneity of farmers' preferences towards agri-environmental schemes across different agricultural subsystems', *Journal of Environmental Planning and Management*, Vol. 60, (2017b) pp. 684–707.

Villanueva, A.J., Rodríguez-Entrena, M., Gómez-Limón, J.A. and Palomo-Hierro, S. 'Report on valuation results (Deliverable 4.2)', PROVIDE Project (No. 633838), 2017c. Available online at: http://www.provide-project.eu/#publications-section (last accessed 30 May 2017).

Westhoek, H. J., Overmars, K. P. and van Zeijts, H. 'The provision of public goods by agriculture: Critical questions for effective and efficient policy making', *Environmental Science & Policy*, Vol. 32, (2013) pp. 5–13.

White, B. and Hanley, N. 'Should we pay for ecosystem service outputs, inputs or both?', *Environmental & Resource Economics*, Vol. 63, (2016) pp. 765–787.

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