Factors Influencing Farmers' WTA Innovative Carbon Farming Contracts For Environmental Improvements

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ABSTRACT: Carbon Farming (CF) practices represent a promising pathway to enhance carbon storage in vulnerable agricultural areas. This study addresses the knowledge gap in the design and acceptability of Agri-Environmental and Climate Schemes (AECS) by examining how tailored CF contracts can promote sustainable practices. Focusing on Liguria, Italy, it explores farmers' preferences for hypothetical CF measures and the factors shaping their willingness to accept. A Discrete Choice Experiment (DCE) with 93 farmers, analyzed through a Conditional Logit Model, shows that farmers prioritize individual over collective participation and prefer both hybrid and result-based payment structures over action-based schemes, with a Wald test confirming that hybrid and result-based contracts are statistically indistinguishable. A Latent Class Model identifies two distinct segments: the first (35.3%) shows strong aversion to collective arrangements and high prescription sensitivity, with membership positively linked to a Benefit-Oriented Management Approach; the second (64.7%) does not significantly discriminate against collective arrangements and is primarily distinguished by a consistent preference for performance-linked payments. Findings underline the need for AECS that reflect diverse farmer preferences, prioritize individually structured and performance-linked contract designs, and ensure adequate compensation to support participation in marginal agricultural areas.

Keywords: *Carbon Farming, Choice Experiment, Agri-Environmental and Climatic Schemes, Willingness to Accept, Innovative Contracts*

JEL Codes: Q54, Q12, Q58

1. Introduction

1.1. Research Scope & Objectives

Carbon Farming (CF) has emerged as a promising pathway to enhance agriculture's role in climate change mitigation. As part of its Fit for 55 package, the European Union (EU) has set ambitious targets for carbon sequestration and greenhouse gas (GHG) reduction, strengthening financial incentives for sustainable land management (European Commission, 2021). However, existing Agri-Environmental and Climate Schemes (AECS) under the Common Agricultural Policy (CAP) have struggled to efficiently drive environmental improvements due to weaknesses in contract design, incentive mechanisms, and farmer behavioral patterns.

This study explores how innovative contractual arrangements can improve the effectiveness of CF policies by aligning farmers' incentives with climate objectives. Using a Discrete Choice Experiment (DCE) in Liguria, Italy, we analyze farmers' willingness to accept (WTA) compensation for adopting CF practices under different contract types, including action-based, result-based, and hybrid schemes. Specifically, the study pursues the following objectives; (i) quantify farmers' WTA for different CF contract attributes, (ii) assess attributes influencing farmers' participation, (iii) examine the role of socioeconomic and behavioral characteristics in shaping preference heterogeneity, (iv) identify latent classes of farmers with distinct preference patterns, providing insights for better policy design.

We hypothesize that (i) farmers will prefer action-based contracts over hybrid and results-based schemes, with higher compensation required for the latter due to perceived risks. (ii) Individual participation is expected to be favored over collective or supply-chain arrangements, which may hinder adoption unless accompanied by stronger incentives. We also expect (iii) that stricter prescriptions will lower participation, but this effect can be offset by higher payments.

1.2. Background: Carbon Farming & Agri-Environmental and Climate Schemes (AECS)

CF refers to a set of land-use and management practices aimed at reducing emissions or increasing carbon sequestration in natural sinks such as soil and vegetation (Smith et al., 2007). In the EU, CF is integrated into AECS under the second pillar of the CAP (Rural Development). These schemes provide voluntary payments to farmers to implement environmentally-friendly practices, compensating for costs incurred and income forgone (D'Alberto et al., 2024). However, AECS have failed to ensure sufficient environmental improvements due to information asymmetries and weak incentive structures (Ansell et al., 2016; Bartolini et al., 2021). Farmers possess superior knowledge of local costs and ecological impacts compared to policymakers, leading to adverse selection (where less effective participants enter contracts) and moral hazard (where compliance is difficult to enforce) (Vergamini et al., 2020).

Traditional action-oriented schemes, which compensate farmers based on prescribed practices rather than environmental outcomes, exacerbate these inefficiencies. Since they rely on private information that farmers may be unwilling to disclose, policymakers face difficulties in targeting the right farmers, particularly in marginal areas with high monitoring costs (Ducos et al., 2009; Espinosa-Goded et al., 2012).

1.3. The Need for Innovative Contractual Approaches

The CAP 2023-2027 introduces new instruments and provides Member States with increased flexibility within their Strategic Plans to design more outcome-oriented and collaborative AECS (COWI et al., 2021; European Commission, 2021). While the CAP does not mandate uniform result-based or collective contract typologies at EU level, it creates enabling conditions for their voluntary adoption. Key emerging approaches include the following.

Collective implementation contracts involve groups of landowners collaborating to achieve shared environmental goals, reducing transaction costs and fostering knowledge exchange (Andersen et al., 2023; Olivieri et al., 2021).Result-based schemes link payments to measurable environmental outcomes, enhancing efficiency and incentivizing innovation (Matzdorf & Lorenz, 2009; Gibbons et al., 2011). However, challenges remain regarding delayed reimbursements and measurement uncertainty (Demeyer et al., 2022).Hybrid contracts combine action- and result-based elements, offering risk-sharing features that may appeal to risk-averse farmers (Gars et al., 2024; Tyllianakis et al., 2023).

A growing body of DCE research examines farmers' preferences across these contract types. Block et al. (2024a) find that German farmers significantly prefer action-based over result-based schemes for carbon sequestration, with participation approximately twice as likely under action-based approaches. Block et al. (2024b) further document how payment thresholds and repayment risks discourage participation. Gars et al. (2024) compare practice-based, hybrid, and result-based agri-environmental schemes across three OECD countries, finding that farmers generally prefer practice-based schemes for climate mitigation goals. These studies provide important international benchmarks against which our Ligurian findings can be contextualized. Our study addresses an identified gap by applying a DCE in a marginal Mediterranean context, focusing on farmers' WTA and preference heterogeneity for different CF contract types.

2. Methodology

2.1. Data Collection

Data were collected in Liguria, a mountainous region in northwestern Italy with a unique topography and a 350 km coastline. The case study region was selected because of its marginal land market activity (Sallustio et al., 2018), specific agricultural practices, susceptibility to hydrogeological instability (Brandolini et al., 2016), and vulnerability to climatic and human-induced changes in the Apennine Mountains (Rellini et al., 2019). These vulnerabilities threaten its natural terrain and rural heritage, making sustainable land management crucial (Vergamini et al., 2024).

The sample included farmers registered with the Liguria farmer association, covering approximately 90% of the regional farming population, ensuring comprehensive regional representation. A survey of 94 farmers, divided into three main DCE blocks, collected data through a questionnaire with three sections: (i) structural and socioeconomic details; (ii) assessments of farmers' perceptions of innovative contract solutions; and (iii) the choice experiment, where farmers selected from four hypothetical choice sets. One respondent was excluded from the DCE due to missing choice-task data (no card version assigned), resulting in a final sample of 93 valid respondents. Since each respondent completed four choice tasks with three alternatives each — two labeled options plus an opt-out — the econometric dataset comprised 1,116 observations ($93 \times 4 \times 3$). All analyses were conducted using Stata 19.5.

2.2. ***Survey Design***

During the survey, before presenting the choice experiment, farmers were given an introduction to ensure a shared understanding of the task. CF was defined as a set of agricultural practices aimed at increasing carbon sequestration and reducing greenhouse gas emissions, including reduced or no tillage, cover cropping, planting trees or landscape elements, afforestation or agroforestry, integrated livestock–crop systems, and the conversion of arable land into permanent grasslands. The introduction emphasized that CF is a central theme in the reform of the CAP and represents a priority measure within the European Green

Deal and Farm to Fork strategy. Respondents were informed that their answers to the hypothetical contract design would contribute to policy recommendations for regional and European agri-climate-environmental measures.

To reduce potential hypothetical bias, a well-documented limitation of stated preference methods including DCEs (Colombo et al., 2022), a short 'cheap talk' script was included prior to the choice tasks (Appendix A5). The script stressed that although the scenarios were hypothetical, they should be answered as if they were real programs with actual implications, and that selecting the 'no participation' option represented a genuine opt-out. The cheap talk approach follows mitigation guidance in Mariel et al. (2021). Nevertheless, we acknowledge that cheap talk alone may not fully eliminate hypothetical bias, and this is discussed further in the limitations section.

2.3. Discrete Choice Experiment: Attributes and Levels

DCEs are widely applied to assess farmers' WTA for different AECSs (Lankoski, 2022, Schulze et al., 2023). They are primarily used to elicit farmer preferences, and can additionally capture the influence of farm characteristics and behavioral factors on decision-making (Massfeller et al., 2022; Niskanen et al., 2020). DCEs also inform hybrid contract designs that combine action- and results-based approaches (Wuepper & Huber, 2021; Gars et al., 2024).

Attributes and levels were selected based on: (i) a review of prior DCE studies on AECS (Raina et al., 2021; Hanley et al., 2001; Wuepper & Huber, 2021; Massfeller et al., 2022; Block et al., 2024a, 2024b); (ii) alignment with existing European and Italian agri-environmental measures, including CAP eco-schemes and the regional RDP; and (iii) restriction of levels to minimize respondent fatigue while maintaining statistical efficiency. Four attributes were identified: participation mode, type of payment, level of payment, and level of prescription. These are presented in Table 1.

Table 1. Attributes and Levels used in the CE

Participation in the measure	Contractual obligation	1) Individual 2) Only with other farmers 3) Only with other supply-chain actors
Type of payment	Type of payment based on justification	1) Only based compensated costs 2) 50% of compensation cost + 50% based on results 3) 100% based on results
Level of payments	Hypothetical remuneration per hectares unrolled under the measure	1) 100 € 2) 200 €
Level of prescription	Expected annual cost to participate in the measure	1) Low 2) Medium 3) High

Regarding the payment levels, it is important to acknowledge that 100 and 200 €/ha represent simplified anchors derived from the regional RDP payment structure. These ranges intentionally capture the lower end of AECS compensation, consistent with the marginal farming conditions in Liguria. As such, the WTA estimates should be interpreted within this regional context rather than as universal benchmarks. The hybrid payment option (50% action-based + 50% result-based) is operationalized as a risk-sharing arrangement where half of the compensation is guaranteed upon practice adoption and half is contingent on measured environmental outcomes, following the design logic of Gars et al. (2024).

The participation attribute combines three qualitatively distinct institutional arrangements. While these differ in coordination complexity and governance structures, they are treated as alternatives within a single dimension to reflect real-world CAP scheme options. Farmers encountered 12 choice tasks, each presenting two contract alternatives (A and B) and an opt-out option (‘no participation’) embedded in the choice card rather than shown as a third column. An example choice card is presented in Appendix A3.

2.4. Econometric Model

After the data has been collected, statistical analysis must be performed to infer the preferences of the respondents (Weber, 2019). The alternative that respondents select or prefer in a DCE choice task is associated with the one that has the greatest net benefit. The econometric analysis relies on the theory of preferences known as Random Utility Theory (RUT) (McFadden, D. 1974). According to this latter theory, the utility that an individual n gets from an alternative j, u_{nj}, is given by a deterministic component, V_{nj}, with an unobserved component, ϵ_{nj} (Train, 2009):

$$u_{nj} = V_{nj} + \epsilon_{nj} \quad (1)$$

Furthermore, this deterministic component of utility can also be formed from both characteristics of the alternatives x_{nj}, multiplied by the levels assigned to each attribute β_{nj}, hence the relationship becomes as follows:

$$u_{nj} = (x_{nj})(\beta_{nj}) + \epsilon_{nj} \quad (2)$$

where beta values can be computed according to different assumptions. For example, if we assume that farmers' preferences are homogeneous, the equation can be written as:

$$u_j = (x_j)(\beta) + \epsilon_j \quad (3)$$

For better computation and data analysis, while taking into account heterogeneity among farmers, the utility will be specified as follows:

$$u_{nj} = (x_j)(\beta_{nj}) + \epsilon_{nj} \quad (4)$$

where utility does not differ between farmers but does differ between alternatives. The Conditional Logit Model (CLM) (Hauber et al., 2016) is used to generate the same coefficients for all respondents. While the CLM is a reliable and simple, it has some limitations and drawbacks such as assuming preference homogeneity and ignoring the panel nature of the data (Pérez- Troncoso, 2020). Although more advanced models such as the Mixed Logit (MXL) are widely used to capture random taste variation, their reliable estimation requires relatively large sample sizes because the identification of variance and covariance parameters is difficult with fewer than 100 respondents (Train, 2009).

The heterogeneity can be attributed to the farmers' different socioeconomic and spatial characteristics, as well as their attitudes, which influence their decision-making (Kanchanaroek & Aslam, 2018). Hence, a Latent Class Model (LCM) was utilized to identify this preference heterogeneity.

Whereas, a LCM is a flexible method that takes into account heterogeneity through the classification of farmers into segments while predicting their choice behavior accordingly (Kanchanaroek and Aslam, 2018).

The LCM is considered as a random utility model where n belongs to a latent class s = (1,2, … , S). Hence, the utility function becomes as follows:

$$u_{ni|s} = (x_{ni})(\beta_s) + \epsilon_{ni|s} \qquad (5)$$

where, x_{ni} represents the attributes appearing in the utility function, and β_s being a segment-specific parameter vector, while $\epsilon_{ni|s}$ represents the random variation for the farmer n. Swait (1994), refers to the error terms as being assumed to be distributed independently across individuals and segments. Therefore, the probability a farmer n belongs to a segment s by choosing alternative i is given by:

$$P_{ni|s} = \frac{e^{\beta_s x_{ni}}}{\sum_i e^{\beta_s x_{ni}}} \qquad (6)$$

The LCM calculates joint probability by taking into account both segment membership and choice, $P_{nis} = (P_{ni|s})(P_{ns})$, where $P_{ns} = \frac{e^{\alpha\lambda_s}}{\sum_{s=1}^{S} e^{\alpha\lambda_s}}$ with λ_S denoting a vector of segment-specific parameters and α being a scale factor assumed to be one, each respondent has a probability of belonging to a specific segment (Boxall and Adamowicz, 2002). Hence, after adding P_{ns} to the probability expression provides the marginal probability of observing farmer n in segment s choosing alternative i:

$$P_{ni|s} = \sum_{s=1}^{S} \left[\frac{e^{\beta x_{ni}}}{\sum_i e^{\beta x_{ni}}}\right]\left[\frac{e^{\alpha \lambda_s}}{\sum_{s=1}^{S} e^{\alpha \lambda_s}}\right] \tag{7}$$

Where the probability of selecting alternative i equals to the sum of all latent classes s of the class-specific membership model conditional on the product of class $P_{ni|s}$ and the probability to belong to that class P_{ns} (Swait, 1994).

To estimate the WTA, the marginal rate of substitution for each level over the payment coefficient was computed as the ratio of the coefficients of attribute levels over the payment coefficient derived from Eq.6

$$WTA = -\frac{\beta_{attribute}}{\beta_{payment}} \tag{8}$$

Where $\beta_{attribute}$ is the estimated coefficient of the attribute level, and $\beta_{payment}$ is the coefficient of the payment variable (e.g. compensation or cost).

2.5. Data Analysis Method

Socioeconomic and farm characteristics were examined using descriptive statistics and ANOVA. Prior to the CE, farmers were presented with four contract typologies to assess their understandability, applicability, and perceived economic benefits (Appendix A 1). A set of 13 Likert scale statements (1 = 'Decreases my willingness considerably' to 5 = 'Increases my willingness considerably') measured farmers' orientations towards contract features.

Principal Component Analysis (PCA) was applied to these 13 statements to reduce dimensionality and address multicollinearity (Gwelo, 2019). Prior to PCA, Bartlett's test of sphericity and the Kaiser-Meyer-Olkin (KMO) measure confirmed data suitability. The Kaiser Criterion retained components with eigenvalues above 1. Orthogonal Varimax rotation was applied with a loading threshold of 0.30. Factor scores derived from the PCA were incorporated as class membership covariates in the LCM, following Chinedu et al. (2018).

They were not included in the CLM utility function, as they represent stable farmer orientations rather than alternative-specific attributes.

3. Results & Discussion

3.1. Socioeconomic and farm characteristics

Table 2 presents the sample characteristics (N = 94 for descriptive statistics; N= 93 for the DCE due to one incomplete response). The majority of the respondents were male (54.26%), with an average age between 41 and 60 years old. Most held primary (45.74%) or upper secondary education (37.23%). Crop farming was the dominant specialization (54.25%), and 82.98% did not practice organic production. Over 72% owned less than 2 hectares, reflecting the small-scale, fragmented structure of Ligurian agriculture. Importantly, less than 10% of total household gross revenue came from farming for 35.11% of respondents, underscoring the marginal economic role of agriculture. Around 29.79% of farms above 20 ha were enrolled in AECS.

In terms of recent environmental improvements, 93.48% of farmers had improved their farm's landscape and scenery, 66.29% had implemented soil quality measures, and 64.13% had adopted carbon storage measures, suggesting a receptive audience for CF-related schemes.

Table 2. Socioeconomic and farm characteristics

		Frequency (N=94)	**Percentage**
Gender	Male	51	54.26
	Female	43	45.74
Age	18-20	-	-
	21-30	8	8.51
	31-40	14	14.89
	41-50	19	20.21
	51-60	21	22.34
	61-70	16	17.02
	71-80	11	11.7
	More than 80	5	5.32
Education level	Primary (elementary school) or lower secondary (primary school)	43	45.74
	Upper secondary education (high school)	35	37.23
	Post-secondary non-tertiary education or short-cycle tertiary education	4	4.26

	Higher education (or tertiary education)	10	10.64
	Not elsewhere classified	1	1.06
Specialization of the holding	Crop farming	51	54.25
	Livestock farming	13	13.83
	Mixed farming	23	24.47
	Forestry & other land use	7	7.45
Organic	Yes, all products	11	11.7
	Yes, some products	5	5.32
	No	78	82.98
Holding hectares	**Agricultural Land (UAA) Owned**		
	Below 2 ha	68	72.34
	Between 2 & 5 ha	13	13.83
	Between 5 & 10 ha	9	9.57
	Above 10	4	4.26
	Agricultural Land (UAA) Rented-In		
	Below 2 ha	45	47.87
	Between 2 & 5 ha	20	21.28
	Between 5 & 15 ha	17	18.09
	Above 15	12	12.77
	Agricultural Land (UAA) Rented-Out	0	90
Total household gross revenue *(on average)* from farming/forestry	Less than 10%	33	35.11
	10-29%	19	20.21
	30-49%	20	21.28
	50-69%	8	8.51
	70-89%	6	6.38
	More than 89%	3	3.19
Area entered into Agri-environment & Climate Measure *(in ha)*	Below 2 ha	27	28.72
	Between 2 & 5 ha	18	19.15
	Between 5 & 10 ha	13	13.83
	Between 10 & 20 ha	8	8.51
	Above 20 ha	28	29.79
Recent farm environmental improvements *(last 5 years) (% of yes)*	Landscape & Scenery	86	93.48
	Biodiversity	45	50
	Soil Quality & Health (e.g. crop diversification)	59	66.29
	Carbon Storage in Soils	59	64.13
	Water Quality	12	13.79

3.2. PCA Components

Following PCA, four components were extracted (Table 3). The Collective Approach (PC1) reflects farmer orientations toward collective agreements on environmental targets, joint payment distribution, and coordinated landscape-level management. The Benefit-Oriented Management Approach (PC2) captures preferences for performance-linked payments, freedom in management practice choice, and environmentally labelled product marketing. The Self-Assessment Preference Approach (PC3) reflects preferences for self-monitoring of environmental outcomes and resistance to external competent authority controls. The Environmental Lease Advocates (PC4) reflects willingness to lease land at reduced rents in exchange for environmental management obligations paired with annual compensation payments. These constructs capture farmers’ orientations toward environmental management and contract participation, and they were later used as covariates in the LCM to explain heterogeneity in class membership. They were not included in the CLM, as they represent stable farmer characteristics rather than attributes of the contract alternatives. A similar approach was taken by Chinedu et al. (2018), who incorporated attitudinal variables as class membership covariates in a latent class model while excluding them from the CLM.

Table 3. Principal component analysis (PCA)

Statements	Rotated Masked PCA			
	Collective Approach (pc1)	Benefit Oriented Management Approach (pc2)	Self-Assessment Preference Approach (pc3)	Environmental Lease Advocates (pc4)
1. In the contract, you are free to decide about the management practices to achieve the specified environmental result.	0.0076	**0.5521**	0.0508	-0.0930
2. The payment gets higher, the better your environmental results are	-0.0490	**0.6175**	-0.1731	-0.0315
3. You can collectively agree on environmental targets and measures at landscape-level together with other land managers	**0.4426**	0.0918	-0.1663	0.0613
4. You and other land managers (farmers) receive a common payment. You jointly agree on the distribution of the payment	**0.5394**	0.0253	-0.1401	-0.0631
5. You sell your farm's products labelled as environmentally friendly (e.g. animal welfare products, climate friendly products) when following management measures as prescribed in a processor or retailer contract	-0.0146	**0.3923**	0.2317	0.0742
6. The contract is not paid by public money, instead the compensation that you get for environmentally friendly production is paid by buyers of your products.	0.2955	0.1655	0.0385	0.1298
7. You can lease land with a reduced rent, if you agree to follow environmental management clauses as specified in the lease contract	0.0788	0.1218	0.1075	**0.4348**
8. You can do the monitoring of the environmental results yourself (e.g. count specific plants)	0.1568	-0.0227	**0.5052**	0.1814
9. The results that you achieve are regularly	0.1019	0.0511	**-0.7159**	0.0959

controlled by the competent authority coming onto your farm (e.g. once a year)				
10. You are offered free training and advice that enables you to reach the environmental targets	0.1394	0.2117	0.2547	-0.2047
11. You get a sales guarantee from a processor or retailer in return for implementing environmental measures	**0.3069**	0.0151	0.0871	0.2885
12. You get environmental compensation payment on an annual basis	-0.0735	-0.0653	-0.0577	**0.7476**
13. You get half of the environmental payment at the beginning of the five-year contract period, and half at the end of it	**0.5128**	-0.2372	0.0997	-0.2120
Eigenvalues	4.2948	1.6098	1.3502	1.2149
Accepted factor loadings	> 0.3			
Bartlett test of sphericity				
Chi-square	431.126			
Degrees of freedom	78			
p-value	0.000*			
KMO	0.721			

Statements 1: Decrease my willingness considerably; 5: Increases my willingness considerably
(*) = significant at 5% level
Factor loadings above the threshold of 0.30 are indicated in bold.

3.3. Understandability, Applicability, & Economic Benefit of Innovative Contracts

Before the DCE tasks, farmers evaluated the four contract typologies presented in Appendix A1. For each typology, farmers rated three statements on a 5-point Likert scale: ease of understanding, applicability to their farm, and potential economic benefit (Appendix A4). One-way ANOVA was used to test whether mean ratings differed significantly from the neutral midpoint across the sample. Results are reported in Table 4.

Table 4. Evaluation criteria for the four contract typologies

Evaluation Criteria	Result-Based	Collective	Supply Chain	Land Tenure
Understandability	0.0000*	0.0000*	0.5670	0.1151
Applicability	0.0001*	0.0004*	0.0001*	0.2284
Economically Beneficial	0.0000*	0.0064*	0.6225	0.0023*

(*) = significant at 5% level

Result-based and collective contracts are more easily understood than supply-chain and land tenure contracts. Applicability ratings differ significantly for result-based, collective, and supply-chain contracts, but not for land tenure contracts, suggesting that the latter is perceived as less directly relevant to current farm conditions particularly given that 72.34% of farmers own land below 2 hectares. Economic benefit perceptions differ significantly for result-based, collective, and land tenure contracts. Private transaction costs can hinder the adoption of such contracts if they are perceived as too complex or burdensome (Bartolini et al., 2021). These findings suggest that contract familiarity and perceived applicability vary considerably across typologies, with implications for adoption rates. Collective contracts are seen as economically attractive and ecologically feasible at low transaction costs when adequate expertise is involved (Franks, 2011), while result-based contracts are valued for their ecological targeting and performance-based incentives (Kelemen et al., 2023).

3.4. Conditional Logit Model (CLM) Results

Dummy variable coding follows Table 1 and Appendix A2. A likelihood ratio test confirms the superiority of the full dummy specification over the restricted linear model (LR $\chi^2(2)$ = 15.41, p = 0.0004). Table 5 presents CLM results for N = 93 farmers (1,116 observations), estimated with Stata 19.5.

For the participation attribute, part_d3 (−1.647***) and part_d4 (−2.188***) confirm a clear preference for individual over collective participation consistent with evidence that collective arrangements increase coordination uncertainty (Rodríguez-Entrena et al., 2018) and demand infrastructure that small-scale Ligurian farmers are unlikely to possess (Kelemen et al., 2023; Block et al., 2024b).

Both paytype_d3 (0.946***) and paytype_d4 (0.884***) are positive and significant, indicating higher utility for hybrid and result-based payments over action-based schemes. Contrary to Hypothesis 1, farmers prefer both hybrid and result-based payment structures over action-based schemes, suggesting that performance-linked elements are valued positively rather than viewed as a risk burden in this context. The Wald test further confirms that hybrid and result-based contracts are statistically indistinguishable ($\chi^2(1)$ = 0.08, p = 0.772), meaning no ranking between the two is supported by the data (Gars et al., 2024). The prescription level (presc, −0.428***) reduces participation, while higher payments (pay_level, 0.014***) increase acceptance, consistent with Alló et al. (2015). The opt-out coefficient (none, 1.488**) is significant, indicating that farmers derive positive utility from opting out when contract conditions are unfavorable. Nonetheless, the negative WTA for the opt-out (Table 8) indicates an overall preference for participation when contract conditions are favorable.

Table 5. CLM results (N = 93, observations = 1,116)

Response	Coefficient	Standard error	95% CI
part_d3	−1.6467***	0.2742	[−2.184, −1.109]
part_d4	−2.1882***	0.3127	[−2.801, −1.575]
paytype_d3	0.9461***	0.3311	[0.297, 1.595]
paytype_d4	0.8838***	0.3278	[0.241, 1.526]
presc	−0.4276***	0.1424	[−0.707, −0.148]
pay_level	0.0141***	0.0021	[0.010, 0.018]
none	1.4878**	0.7255	[0.066, 2.910]

(***), (**), (*) denote significance at the 1%, 5%, and 10% level respectively. Reference categories: part_d2 = individual participation; paytype_d2 = action-based payment.

3.5. Latent Class Model (LCM) Results

The appropriate sample size for DCEs remains debated in the literature (de Bekker-Grob et al., 2015; Schulze et al., 2023), with published agri-environmental DCE studies showing considerable variation in sample sizes. Our sample of 93 farmers is consistent with established practice in the field.

The LCM was fitted with PCA factor scores (PC1–PC4) and socioeconomic variables as candidate membership covariates, retaining only statistically significant variables in the final specification. Class selection was based on AIC and BIC (Birol et al., 2008), as presented in Table 6. The three-class model did not achieve convergence, which is consistent with the literature noting that convergence failures are expected when the number of class-specific parameters approaches the limits supported by the available sample size (Weller et al., 2020), independently confirming the two-class solution as optimal.

Table 6. Criteria for optimal class selection

No. of Class	No. of Parameters	Log-Likelihood	AIC	BIC
1	7	−297.742	609.484	644.607
2	14	−250.013	528.026	563.482
3	—	Did not converge	—	—

The two-class LCM identifies two meaningfully distinct farmer segments (Table 7). Class 1 comprises 35.3% of farmers and Class 2 comprises 64.7%. In the parsimonious specification, pay_level and none are constrained as fixed parameters across both classes. This is theoretically appropriate: the marginal utility of payment and the baseline opt-out utility should not vary systematically across latent classes defined by attitudinal orientation.

Table 7. LCM results of the two classes

Utility Parameter	Conditional Logit Model		Latent Class Model Class 1 (35.3%)		Class 2 (64.7%)	
	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
part_d3	−1.647***	0.274	−3.025***	0.795	−1.022	0.572
part_d4	−2.188***	0.313	−5.103***	0.987	−1.081	0.751
paytype_d3	0.946***	0.331	1.699**	0.744	1.061**	0.512
paytype_d4	0.884***	0.328	1.505**	0.740	1.385***	0.501
presc	−0.428***	0.142	−1.230***	0.367	−0.339	0.257
pay_level	0.014***	0.002	0.015***	0.002	0.015***	0.002
none	1.488**	0.725	0.669	1.050	0.669	1.050
Class Membership Function						
constant			0.814	0.556		
Benefit Oriented Management Approach			−1.158***	0.310		
Avg class probability			0.353	0.647		
Log- likelihood function	−297.742		−250.013			
AIC	609.484		528.026			
BIC	644.607		563.482			
Number of observations			1116			

(***), (**), (*) denote statistical significance at the 1%, 5% and 10% level, respectively.

For Class 1, the smaller segment comprising 35.3% of farmers — all key parameters are statistically significant. Participation with other farmers (part_d3, −3.025***) and supply chain actors (part_d4, −5.103***) both significantly reduce utility compared to individual participation, confirming a strong and consistent aversion to collective arrangements. Both hybrid (paytype_d3, 1.699**) and result-based (paytype_d4, 1.505**) payment structures significantly increase utility relative to action-based payments, indicating that farmers in this class respond positively to performance-linked contract elements. The prescription level (presc, −1.230***) significantly reduces willingness to participate, reflecting high sensitivity to compliance burden. In the class membership equation, the Benefit-Oriented Management Approach (PC2, −1.158***) is negative and significant, confirming that farmers with higher PC2 scores — those who value autonomy in practice selection, higher payments linked to environmental performance, and eco-labelling — are significantly more likely to belong to Class 1 than Class 2. This aligns with Whittingham (2011), who emphasized that farmer autonomy and advisory support are critical determinants of agri-environmental scheme participation.

For Class 2, the larger segment at 64.7% as the preference pattern is notably different. Aversion to collective participation is directionally negative but not statistically significant for either farmers (part_d3, −1.022, $p = 0.074$) or supply chain actors (part_d4, −1.081, $p = 0.150$), suggesting that this group does not systematically discriminate against collective arrangements. Both hybrid (paytype_d3, 1.061**) and result-based (paytype_d4, 1.385***) payment types remain significantly preferred over action-based payments, indicating that the preference for performance-linked payments is a consistent finding across both classes. The prescription level is not significant in Class 2 (presc, −0.339, $p = 0.188$), indicating that compliance burden is not the primary driver of this class's participation decisions. The key distinguishing feature of Class 2 relative to Class 1 is therefore the absence of strong aversion to collective arrangements and prescription sensitivity, suggesting that these farmers may be more open to innovative collective contract designs provided payment conditions are favorable.

The membership equation reveals that lower PC2 scores predict membership in Class 2, meaning farmers who are less oriented toward benefit-driven autonomy and eco-labelling are more likely to belong to this larger segment. This is confirmed by the mean PC2 score in Class 1 (2.117) being substantially higher than in Class 2 (−0.617). These findings suggest that contract design for Class 2 farmers should prioritize payment level and payment type, particularly result-based elements, while Class 1 farmers additionally require individual participation structures and lower prescription burdens to engage.

3.6. Farmers Willingness to Accept (WTA) for Carbon Farming Measures

Table 8. Farmers WTA for CF measures

Attributes	WTA (€/ha)	95% CI
Participation: collective w/ farmers vs. individual	116.64***	[63.62, 169.67]
Participation: supply chain actors vs. individual	155.01***	[90.19, 219.82]
Payment type: hybrid vs. action-based	−67.02***	[−111.50, −22.54]
Payment type: result-based vs. action-based	−62.61***	[−107.61, −17.60]
Prescription level (per unit increase)	30.29***	[7.39, 53.19]
None (opt-out)	−105.39**	[−187.61, −23.18]

(***), (**), (*) denote statistical significance at the 1%, 5% and 10% level, respectively.

Farmers require an additional €117/ha to participate with other farmers and €155/ha to engage with supply chain actors, highlighting a strong reluctance toward collective and externally coordinated arrangements unless substantial compensation is provided. These estimates are consistent with Block et al. (2024b), who found that farmers in German carbon sequestration programs required significant financial incentives to overcome aversion to collective participation, and with Rodríguez-Entrena et al. (2018), who documented similar resistance to coordination-intensive schemes among small-scale farmers.

With respect to payment type, both hybrid (−€67/ha) and result-based (−€62/ha) contracts require less additional compensation than action-based ones, indicating that farmers are willing to accept a modest reduction in guaranteed payment in exchange for performance-linked elements. Critically, the Wald test confirms that these two WTA values are statistically indistinguishable ($\chi^2(1) = 0.08$, $p = 0.772$), meaning the data do not support a ranking between hybrid and result-based contracts. This is consistent with Gars et al. (2024), who found that the advantage of practice-based over hybrid and result-based contracts was consistent but the difference between hybrid and result-based was not statistically robust.

Stricter prescription requirements demand approximately €30/ha additional compensation, reflecting the burden of higher compliance costs on farmers who already operate in constrained marginal conditions. The opt-out WTA of −€105/ha indicates that, conditional on receiving reasonable contract conditions, farmers prefer participation over non-participation — the negative sign means they would accept €105/ha less than the full payment rather than opt out entirely. This overall preference for participation, even at reduced compensation, is an encouraging signal for policy design in marginal areas such as Liguria. Vergamini et al. (2024) similarly demonstrate that in Liguria, policy mixes combining mandatory CAP measures with voluntary result-based payments can achieve significant reductions in soil erosion and land abandonment, reinforcing the importance of adequate financial design as a precondition for farmer engagement.

4. Limitations

Several limitations must be acknowledged. First, the sample is region-specific and based on farmers' association membership in Liguria. While this enables near-complete coverage within the target population, findings cannot be straightforwardly generalized to other Italian regions or broader European contexts with different farming structures, payment environments, or policy frameworks.

Second, all DCE studies are susceptible to hypothetical bias: despite the cheap talk script, stated preferences may deviate from actual behavior (Colombo et al., 2022). Single-strategy mitigation is unlikely to be fully sufficient, and this limitation should be considered when translating WTA estimates into policy recommendations.

Third, the PCA-derived attitudinal components used as LCM covariates carry a risk of endogeneity: farmer orientations toward contract features (e.g., self-monitoring, collective engagement) may not be fully independent of the choice experiment stimuli. Future research could address this through pre-registered survey instruments that separate attitudinal measurement from choice stimuli.

Fourth, self-selection into the farmers' association may introduce selection bias: non-affiliated farmers, who may hold systematically different preferences or face different constraints, are not represented. Future studies with larger, more diverse samples would help to validate and extend these findings.

Fifth, while the payment levels of 100 and 200 €/ha are grounded in the regional RDP context, the absence of pilot testing with farmers means their perceived realism has not been independently validated. The inclusion of only two payment levels also limits utility balance and WTA precision; future DCE designs should consider a wider payment range.

5. Policy Recommendations & Conclusion

This study examined farmers' preferences for innovative contracts incentivizing carbon farming (CF) practices in Liguria. A DCE with 93 farmers showed a preference for individual over collective participation and higher utility for both hybrid and result-based payment structures over action-based schemes, with a Wald test confirming that hybrid and result-based contracts are statistically indistinguishable. The LCM identified two distinct segments: Class 1 (35.3%) shows strong aversion to collective arrangements and high prescription sensitivity, with membership positively linked to a Benefit-Oriented Management Approach; Class 2 (64.7%) does not significantly discriminate against collective arrangements and is primarily distinguished by a consistent preference for performance-linked payments.

Farmers' WTA indicated that collective participation requires substantial additional compensation, while hybrid and result-based contracts carry statistically indistinguishable

WTA values, reflecting similar perceived risks. The negative WTA for the opt-out confirms an overall preference for participation when conditions are favorable. These findings suggest that without considering farmers' behavioral patterns, innovative contracts risk policy failure, particularly in vulnerable marginal areas. Effective implementation requires complementing contract design with advisory services that reduce uncertainty and build trust (D'Alberto et al., 2024), drawing on evidence that policy mixes combining mandatory and voluntary measures can reduce soil erosion and land abandonment in Liguria (Vergamini et al., 2024).

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