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Volumetric choice experiments and welfare measures in a subsidy-driven context

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ABSTRACT

Volumetric Choice Experiments (VCE) offer a novel approach to studying individual behavior, traditionally explored through Discrete Choice Experiments. This study assesses the efficacy of VCE in understanding farmers' preferences regarding new results-based and practice-based agri-environmental contracts, using a comprehensive international stated preference survey. Recognizing that farmers often act as households maximizing utility rather than purely profit-driven producers, we provide justification for applying a utility-based framework in this context. The subsidy-driven nature of agri-environmental contracts poses a challenge for the use of multiple discrete-continuous choice models suited for VCE data. Conventionally, these models utilize an income-based budget equation, which would not be binding given the willingness-to-accept format of the experiment. To operationalize our model, we adopt a land-based budget equation, facilitating the development of a novel compensating variation measure for welfare analysis. Our findings reveal insightful contrasts between VCE-derived data and traditional DCE results, highlighting the complexities encountered and the comparability of outcomes. By delving into the distinct attributes of VCE and justifying the utility-based approach for farmers, this research not only bridges a critical gap in the literature but also enhances our understanding of farmer behavior, with significant implications for the design and implementation of future agri-environmental policies.

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1. Introduction

Volumetric Choice Experiments (VCEs), as conceptualized by Carson et al. (2022), offer an innovative way to observe the trade-offs individuals are willing to make across attributes of a good. Unlike standard Discrete Choice Experiments (DCEs), VCEs ask respondents not only to select among labeled alternatives but also to allocate *quantities* across them. This additional continuous dimension enables a more granular mapping from attributes to choices and can yield a more accurate depiction of preferences. The approach is particularly apt when real-world decisions are inherently continuous – such as farmers' enrollment decisions in agri-environmental contracts – where land can be partitioned across multiple schemes. Capturing such behavior in a standard DCE would require post-hoc assumptions or follow-up questions (e.g., Tanaka et al., 2022), whereas a VCE observes the allocation directly.

Applying VCEs typically requires econometric models that differ from those used with DCE data. A natural workhorse is the Mixed Multiple Discrete–Continuous Extreme Value (MMDCEV) model (Bhat, 2008), which accommodates multiple corner solutions and continuous allocations. However, the canonical MMDCEV relies on an income-based budget constraint and is usually interpreted in a willingness-to-pay (WTP) frame. In agri-environmental settings, where payments are *subsidies* rather than prices, farmers' enrollment decisions are better represented in a willingness-to-accept (WTA) frame and constrained by *land*, not income. We therefore operationalize an MMDCEV with a land-based budget, and develop a choice-task-specific compensating-variation (CV) measure suitable for subsidy contexts. Because participation decisions in our application concern both household welfare and production choices, we also justify – up front – a utility-based farm-household model in which farm profit is one argument of utility. This addresses common concerns about treating farmers solely as profit-maximizing firms and aligns the MMDCEV with the behavioral context analyzed in Section 2.

While our contribution is mainly methodological, the policy context matters for both design and interpretation. Across Europe, agri-environmental-climate measures (AECM) are central to aligning agriculture with biodiversity and broader environmental goals under the Common Agricultural Policy (CAP). Yet despite substantial investment and successive reforms, ecological performance remains mixed, and scaling promising instruments beyond pilots has proven difficult – especially on arable land. A core design choice, long debated in environmental and resource economics, is whether to pay for inputs (practices) or outputs (results). Input-based (practice- or action-oriented) contracts condition payments on prescribed management actions. They are administratively familiar and relatively easy to monitor, but their link to ecological outcomes can be weak, raising additionality concerns. Output-based (results- or outcome-oriented) contracts, by contrast, tie payments to measured environmental performance. In theory, they harness producers' private information about local biophysical conditions and technologies and can improve cost-effectiveness. In practice, they expose farmers to outcome risk (ecological variability, measurement noise) and place greater demands on monitoring, indicator design, and enforcement – classic problems of incomplete information and limited observability (Bontems and Bourgeon, 2000; Gulati and Vercammen, 2006).

These trade-offs sharpen on arable land. Practice-based contracts provide legal certainty and low litigation risk, but target conservation only indirectly. Results-based contracts can reward what society ultimately cares about – habitat quality and species presence – yet shift stochastic performance risk to the farm household and require robust, transparent indicators and credible monitoring protocols. They also raise risk-sharing and time-consistency questions when outcomes depend on weather or neighboring actions or when political pressure threatens ex-post renegotiation of rewards (Gulati and Vercammen, 2006). Over the last two decades, European pilots have demonstrated feasibility of results-based designs in some settings (e.g., species-rich grasslands), and hybrid formats that add landscape-level collective bonuses have emerged to align incentives when ecological benefits depend on spatial coordination. Even so, upscaling beyond pilot conditions remains limited on cultivated arable land due to heterogeneous ecological priorities, indicator reliability and cost, administrative capacity constraints, and farmers' concerns about fairness and income volatility (e.g., Burton and Schwarz, 2013; Uthes and Matzdorf, 2013; McLoughlin et al., 2020; Natural England, 2020; Herzon et al., 2018).

Designing AECM that can scale requires credible ex-ante evidence on farmers' preferences for input- versus output-based designs, on the role of risk and trust in monitoring, and on how farmers would allocate land across multiple contracts concurrently. Standard DCEs recover the most-preferred label but rarely observe the continuous allocation that policy needs for acreage forecasts and budget planning. VCEs fill this gap by eliciting hectare allocations across practice-based, results-based, and status-quo options. In subsidy-driven WTA contexts, VCEs are also appealing because land – not income – is the binding constraint. Together with an MMDCEV estimated under a land constraint, VCEs allow policy-relevant predictions of uptake and welfare under alternative contract designs.

Against this backdrop, our study makes two sets of contributions. Methodologically, we adapt the VCE–MMDCEV framework to subsidy contexts by: (i) implementing a land-based budget; (ii) estimating a mixed specification to capture preference heterogeneity; and (iii) proposing and operationalizing a CV measure tailored to VCE data. Substantively, we field a multi-country VCE (Germany, the Netherlands, Poland, and Czechia) on farmers' preferences for practice- versus results-based biodiversity contracts on arable land and include a collective, landscape-level results-based bonus. The empirical patterns we document – strong responses to mean annual and bonus payments, limited average response to payment ranges (uncertainty), and sizable heterogeneity – speak directly to the obstacles that have hampered the upscaling of results-based schemes and to the design features that might improve their acceptability.

The remainder of the paper proceeds as follows. Section 2 develops the conceptual and econometric framework, including our utility-based household justification, the MMDCEV with a land budget, and algorithms for prediction and welfare calculation. Section 3 describes the survey and VCE. Section 4 reports model estimates, elasticities, and welfare measures. Section 5 concludes with implications for the design – and scaling-up – of results- and practice-based contracts under the CAP.

2. Methodology

We aim to develop a framework for analyzing farmers' preferences by combining VCE data with a multiple discrete-continuous choice model and compare it against the standard approach used for the analysis of DCE data. In Section 2.1, we provide a justification for using a utility-based setting for studying farmers, who could be considered producers rather than consumers. In Section 2.2 we briefly introduce a mixed logit model, which is a state-of-the-art approach for analyzing DCE data. In Section 2.3 we then introduce the MMDCEV model as well as the methods employed to obtain predictions and welfare measures from it.

2.1. Theoretical justification for using a utility function for farm households

Utility functions are fundamental in microeconomics for modeling decision-making processes where individuals or households aim to maximize their satisfaction or utility subject to constraints (Mas-Colell et al., 1995). Initially defined for individuals (consumers), this concept has been extended to households, where utility functions represent the collective welfare of all members, encompassing both consumption and leisure activities (Samuelson, 1956; Becker, 1993).

Within agricultural economics, the random utility framework is usually the method of choice when studying the behavior of farmers (e.g., Espinosa-Goded et al., 2010; Costedoat et al., 2016; Latacz-Lohmann and Breustedt, 2019; Tanaka et al., 2022). Even though farmers are formally producers rather than consumers, this assumption is rarely discussed. This is surprising given that the question about the appropriate framework was raised 50 years ago (Lin et al., 1974). In what follows, we argue that in the case analyzed in this paper, treating farmers as households with a utility function – in which the farm's profit enters as one of the arguments – is more fitting.

The traditional "unitary model" of household behavior assumes that a household, even if it consists of different individuals, acts as a single decision-making unit aiming to maximize a collective utility function. This model simplifies the analysis by assuming that all household members have aligned preferences and share common objectives in consumption, leisure, and income generation (e.g., labor supply). This approach has been extensively used to explore how households allocate resources under budget constraints and has been instrumental in studies related to labor supply, consumption, and savings (Gronau, 1977). These models are often employed to analyze welfare changes due to policy shifts, assuming that any change affecting one member affects all members equally (Lazear and Michael, 1988).[1]

Applying utility functions to farm households extends the traditional unitary model by integrating aspects unique to agricultural settings. Farm households not only make decisions regarding consumption and leisure but also manage agricultural production, which directly influences their livelihood and welfare. This dual role complicates their decision-making processes, as they must balance immediate consumption needs with production decisions that affect future income and food security (Janvry et al., 1991). Furthermore, unlike other businesses, European family farms are typically inherited over generations and have high levels of equity ownership, making them more akin to a household. These dynamics can be captured by extending utility functions to include variables specific to farming, such as crop choices, labor allocation between farm and off-farm activities, and investments in farm capital.

As an alternative approach, profit maximization models assume that farm households prioritize financial returns above other considerations, which is particularly relevant in predominantly market-driven settings (Mendola, 2007). These models focus on the optimal allocation of resources to maximize economic gains from agricultural operations, analyzing farm behaviors closely integrated with markets, as highlighted by Singh et al. (1986). However, this approach may not fully capture the diverse motivations of farm households, especially in environments where economic activities are intertwined with subsistence needs and family welfare. Profit maximization tends to overlook how households might prioritize stability and security, as well as risk aversion and food security, in their decision-making processes, influenced by both market and non-market factors such as cultural practices and environmental conditions (Ellis, 1993).

Crucially, for our specific study on farmers' preferences for environmental outcomes in agri-environmental contracts, the profit maximization model proves inadequate. This model fails to account for non-financial preferences such as biodiversity conservation and ecosystem services – factors that are essential in understanding and predicting farmer behaviors in these contexts. In contrast, a utility function framework is more suitable as it encompasses both financial and non-financial motivations. As demonstrated by Dupraz et al. (2003), the WTA compensation for allocating land to environmental contracts is influenced not only by profit loss but also by the direct utility the household derives from environmental stewardship.

Finally, the appropriate framework for analyzing farmers' behavior will depend on the particular sample and types of farms

[1] While the unitary model simplifies household decision-making by assuming unified preferences, alternative non-unitary models – such as the collective and non-cooperative models – offer nuanced insights into intra-household dynamics by recognizing individual preferences and bargaining power (Molina, 2011). These models, which take into account factors such as income, wealth, and external wage opportunities, are essential for understanding complex interactions and resource distribution within households based on individual bargaining positions (McElroy and Horney, 1981; Chiappori, 1992). They effectively address intra-household allocation of goods and welfare distribution, providing a more accurate framework for predicting behavioral shifts in response to economic or policy changes than the unitary model (Browning et al., 1994; Vermeulen, 2002). Additionally, non-cooperative models based on game theory elucidate scenarios where household members act independently rather than cooperatively. These models highlight the role of individual strategies and conflicts in decisions about public goods consumption and during events like divorce (Manser and Brown, 1980; Lundberg and Pollak, 1993). However, for certain research contexts such as ours, these complex models may not be necessary when simpler unitary assumptions suffice.

studied. In the current study, we utilize an international European sample in which about 78% of farms are either family-owned or individually owned (cf. Table 3). We argue that in such a case, utilizing a household utility framework is more suitable. On the other hand, for farms owned by corporations or in partnership with multiple farmers, profit maximization may be more fitting.

In conclusion, the use of utility functions in our analysis of farm households provides a comprehensive framework that integrates both economic and non-economic factors, essential for a complete understanding of household decisions. This approach is especially advantageous for policy analysis, as it captures the complex dynamics between market behaviors and broader welfare metrics like health and education. Unlike profit maximization models, which often overlook important non-financial preferences such as environmental conservation, utility functions allow for a detailed exploration of how farm households respond to various policy interventions. This makes them a crucial tool in agricultural economics research, offering a balanced perspective necessary for effective policy development that aligns economic incentives with sustainable agricultural practices.

2.2. Mixed logit model

The mixed logit model (MXL) presented in this section is estimated on multinomial choice data created by transforming VCE data into DCE data. Specifically, the transformation is based on the assumption that in the DCE format, farmers would indicate a single contract to which they enrolled the most land in the VCE.[2]

Most modern discrete choice models are rooted in the random utility framework introduced by McFadden (1974). This setting assumes that the choice set consists of a discrete set of mutually exclusive alternatives, from which an individual chooses the one maximizing their random utility. The individual is then assumed to consume a single unit of the chosen good. The random utility function of individual *i*, an alternative *j*, and the choice set *t*, is given by

$$U_{ijt} = \mathbf{X}_{ijt}\boldsymbol{\beta}_i + \lambda_i p_{ijt} + \varepsilon_{ijt}. \tag{1}$$

Here, p_{ijt} is a monetary attribute, for example, the compensation for enrolling into an agri-environmental scheme, whereas $\mathbf{X}_{ijt}$ is a vector of the rest of the attributes. $\boldsymbol{\beta}_i$ and λ_i describe individual-specific marginal utilities, that are unknown to the researcher. Finally, ε_{ijt} is a stochastic term, following an extreme value distribution, which is independent across individuals, alternatives, and choice tasks. For identification its variance and mean are normalized.

Denoting by $\mathbf{y}_i$ a vector of individual's *i* choices, we can write its conditional probability as a product of simple multinomial logit formulas

$$P(\mathbf{y}_i|\boldsymbol{\beta}_i, \lambda_i) = \prod_{t=1}^{T} \frac{\exp\left(\mathbf{X}_{iy_{it}t}\boldsymbol{\beta}_i + \lambda_i p_{iy_{it}t}\right)}{\sum_{j=1}^{J}\exp\left(\mathbf{X}_{ijt}\boldsymbol{\beta}_i + \lambda_i p_{ijt}\right)}. \tag{2}$$

The formula in (2) can be then used to specify a likelihood function. Nonetheless, in most practical applications, there is no sufficient data to estimate parameters $\boldsymbol{\beta}_i$ and λ_i separately for each individual. For this reason, these coefficients are usually treated as random parameters, namely, they are assumed to follow a certain distribution in the population, described by the pdf function $f(\boldsymbol{\beta}_i, \lambda_i|\boldsymbol{\theta})$. Here, $\boldsymbol{\theta}$ is a vector of coefficients to be estimated which describes a said (multivariate) distribution. Such a model is usually referred to as mixed logit, as it is a mixture of simpler multinomial logits. Once the distribution of random parameters is specified, the likelihood function can be then derived as a following integral

$$L(\boldsymbol{\theta}) = \int P(\mathbf{y}_i|\boldsymbol{\beta}_i, \lambda_i) f(\boldsymbol{\beta}_i, \lambda_i|\boldsymbol{\theta}) d\boldsymbol{\beta}_i d\lambda_i, \tag{3}$$

and then optimized to find estimates of $\boldsymbol{\theta}$. As an analytical solution of the above integral is unknown, it is usually approximated by using a quasi-Monte Carlo method. In what follows we employ scrambled Sobol sequence (Czajkowski and Budziński, 2019) to generate quasi-random draws to evaluate integral in (3).

To obtain supply predictions from the MXL model we evaluate two approaches which we label as "*single contract*" and "*probability-based*", and formulate them as follows

$$\begin{aligned} L_{ijt}^{SC} &= \Gamma_i \mathbf{1}_{\{P_{ijt} = \max_k (P_{ikt})\}} \\ L_{ijt}^{PB} &= \Gamma_i P_{ijt} \end{aligned} \tag{4}$$

In (4), Γ_i denotes a total land that is available to a farmer, whereas P_{ijt} denotes probability of choosing contract *j*, as predicted by the MXL model. Basically, the "*single contract*" approach assumes that farmer enrolls all of the available land to the alternative with the highest predicted probability, whereas the "*probability-based*" approach simply assumes that enrollment is proportional to the predicted probability.

Finally, given the utility formulation in (1), the willingness to accept (WTA) can be defined simply as a ratio of coefficients, namely $\mathrm{WTA} = -\beta_i/\lambda_i$.

[2] In cases of equal allocations, the first alternative was assumed to be selected.

2.3. Mixed multiple discrete-continuous extreme value model

To operationalize the household utility specification, we employ the multiple discrete-continuous choice model following Bhat's (2008) framework. In this setting, the farm household can select continuous supply of their land to enroll into multiple agri-environmental contracts, rather than simply selecting the most preferred contract as in the MXL model. We first specify the logarithm of the baseline utility for the j-th contract, in the t-th choice situation for farm i, as

$$V_{ijt} = \mathbf{X}_{ijt}\boldsymbol{\beta}_i + \lambda_i p_{ijt} + \eta_{ijt}. \quad (5)$$

The notation is the same as in (1), with η_{ijt} being a stochastic component, which is assumed to have a (standardized) extreme value distribution. This assumption about the distribution of the error term leads to a multiple discrete-continuous extreme value model (MDCEV). To allow for preference heterogeneity of farm households, we allow the baseline utility coefficients, $\boldsymbol{\beta}_i$ and λ_i, to vary across the farm households, leading to the mixed MDCEV specification. Note that even though the specification in (5) mirrors the one in (1) for the MXL model, the coefficients here have different interpretations and they do not represent marginal utilities.

The utility of farm household i from supplying the vector of land $\mathbf{L}_{it} \in \mathbb{R}_+^J$ into contracts available in choice task t, is given by the function

$$U(\mathbf{L}_{it}|\boldsymbol{\beta}_\mathbf{i}, \lambda_i, \boldsymbol{\alpha}, \boldsymbol{\gamma}) = \sum_{j=1}^{J} \frac{\gamma_j}{\alpha_j} \exp\left(V_{ijt}\right) \left[\left(\frac{L_{ijt}}{\gamma_j} + 1\right)^{\alpha_j} - 1\right]. \quad (6)$$

As already mentioned, $\exp\left(V_{ijt}\right)$ can be considered a baseline marginal utility, namely a marginal utility when the supply level is zero, $L_{ijt} = 0$. $\boldsymbol{\alpha}$ and $\boldsymbol{\gamma}$ are additional coefficients to be estimated, which describe the shape of the utility function. Bhat (2008) recommends putting some constraints on these coefficients, as identifying all of them may be numerically challenging in practice. In what follows, we estimate a full set of $\boldsymbol{\gamma}$, but we constrain $\boldsymbol{\alpha}$ to be equal across contracts ($\alpha_j = \alpha$, for all j).

In the MDCEV framework, farm household i is assumed to maximize (6) with respect to the budget equation

$$\sum_{j=1}^{J} \rho_j L_{ijt} = \Gamma_i. \quad (7)$$

In the usual setting, ρ_j denotes the price of the consumed alternative, and Γ_i denotes the overall income of individual i. In the VCE conducted in the current study, farm households could enroll their land into a set of agri-environmental contracts in exchange for the monetary compensation. As such, there is no "price" for the enrollment, but rather a subsidy. Because of that, the farmers' choices are not bounded by their income. In order to operationalize the MDCEV model for the WTA-based setting of farmers' choice, we propose to use the area of the land in the budgeting equation with "prices" being set to unity, $\rho_j = 1$. Namely, in our case, $\sum_{j=1}^{J} L_{ijt} = \Gamma_i$, with Γ_i denoting a total available land. Therefore, the budget equation boils down to saying that the sum of land enrolled in each contract cannot exceed the total area of available land.

In settings where monetary income is not the binding resource, the MDCEV literature has modeled allocations either in absolute units (e.g., hours, kWh, hectares) or in shares of an endowment that sum to one. For example, in regional freight applications, the decision is often represented as allocating a shipment across modes in percentages (Tapia et al., 2020). In our context, two features argue for an absolute (hectares) constraint: (i) the policy object – both payments and administrative limits – is defined per hectare, and (ii) farmers' land endowments vary widely and are empirically important for behavior (see Section 4.1). A share normalization would remove Γ_i from the resource constraint, implicitly shifting land heterogeneity into the utility and altering the Lagrange multiplier; in practice, this can attenuate the role of Γ_i that we observe in the data. Our land-based formulation keeps the resource in natural units and preserves the structural channel through which Γ_i affects both the intensive margin (hectares enrolled) and welfare.

More broadly, our approach follows other MDCEV applications that replace income with a non-monetary endowment, such as time in activity/time-use modeling and physical quantities in energy demand (Palma et al., 2021; Calastri et al., 2023). Finally, our specification aligns with recent MDCEV advances that emphasize closed-form demand systems and forecasting procedures when the binding resource is not income (Bhat, 2022).[3]

Assuming an extreme value distribution for η_{ijt}, we can derive a closed-form formula for the conditional probability of the farm household choosing $\boldsymbol{L_{it}}$ level of land supply, by maximizing (6), with respect to (7). This formula is given by[4]

$$P(\mathbf{L}_{it}|\boldsymbol{\beta}_\mathbf{i}, \lambda_i, \alpha, \boldsymbol{\gamma}) = (M-1)! \left[\prod_{\substack{j=1 \\ L_{ijt}>0}}^{J} f_{ijt}\right] \left[\sum_{\substack{j=1 \\ L_{ijt}>0}}^{J} \frac{1}{f_{ijt}}\right] \left[\frac{\prod_{j=1;L_{ijt}>0}^{J} \exp\left(\mathbf{X}_{ijt}\boldsymbol{\beta}_i + \lambda_i p_{ijt}\right)}{\left(\sum_{j=1}^{J} \exp\left(\mathbf{X}_{ijt}\boldsymbol{\beta}_i + \lambda_i p_{ijt}\right)\right)^M}\right]. \quad (8)$$

[3] Under restrictive conditions (e.g., homothetic preferences with common translation terms), level- and share-based normalizations can be algebraically close. With contract-specific γ_j and random taste heterogeneity, however, predictions and welfare are not invariant to scaling.

[4] The formula is simplified with respect to the one in Bhat (2008), because we assume unit prices as well as unit variance of the error term.

Here, M denotes the number of contracts for which the land supply is positive. Note that most products and summations in this formula are over alternatives for which $L_{ijt} > 0$. Finally, $f_{ijt} = \left(\frac{1-\alpha}{L_{ijt}+\gamma_j}\right)$.

The probability in (8) is conditional on the individual-specific parameters, $\boldsymbol{\beta}_i$ and λ_i. To obtain unconditional distributions, we need to assume their distribution in the population and integrate them out, analogously as in the case of MXL. This will lead to an MMDCEV specification. The likelihood function is then given by

$$L(\boldsymbol{\theta}, \alpha, \boldsymbol{\gamma}) = \int \prod_{t=1}^{T} P(\mathbf{L}_{it}|\boldsymbol{\beta}_i, \lambda_i, \alpha, \boldsymbol{\gamma}) f(\boldsymbol{\beta}_i, \lambda_i|\boldsymbol{\theta}) d\boldsymbol{\beta}_i d\lambda. \tag{9}$$

We denote coefficients describing the distribution of random parameters by $\boldsymbol{\theta}$. The integral in (9) was approximated using quasi-Monte Carlo simulation, with 10,000 scrambled and shuffled Sobol draws per farm household (Czajkowski and Budzinski, 2019).

2.3.1. Supply predictions

To obtain predictions of the land supply that farm households enroll into a given contract, we follow Pinjari and Bhat (2021). The algorithm is applied on the choice task level for each household and requires generating random draws for error term η_{ijt}, as well as random parameters $\boldsymbol{\beta}_i$ and λ_i. We, therefore, generate R independent draws from the multivariate distribution $f(\boldsymbol{\beta}_i, \lambda_i|\widehat{\boldsymbol{\theta}})$, which we denote by $(\boldsymbol{\beta}_i^r, \lambda_i^r)$. We use $\widehat{\boldsymbol{\theta}}$ to highlight that these are estimates of the true coefficients $\boldsymbol{\theta}$. Similarly, we generate $R \times T \times J$ independent draws from standardized extreme value distribution, which we will denote by η_{ijt}^r. Analogously as in the estimation process, we employ scrambled Sobol draws for the sake of the simulation.

For farm household i, choice task t, and set of draws r, we use the following steps to obtain predictions of $\widehat{\mathbf{L}}_{it}^r$.

1. Calculate the baseline utility for each contract[5]

$$\psi_{ijt}^r = \exp\left(V_{ijt}^r\right) = \exp\left(\mathbf{X}_{ijt}\boldsymbol{\beta}_i^r + \lambda_i^r p_{ijt} + \eta_{ijt}^r\right). \tag{10}$$

2. Sort ψ_{ijt}^r in descending order.
3. To begin with, assume that land is enrolled only into the contract with the highest value of ψ_{ijt}^r. Calculate the value of the Lagrange multiplier

$$\lambda_{it}^r = \left(\frac{\Gamma_i + \sum_{j\in\Omega}\widehat{\gamma}_j}{\sum_{j\in\Omega}\widehat{\gamma}_j\left(\psi_{ijt}^r\right)^{\frac{1}{1-\alpha}}}\right)^{\alpha-1}, \tag{11}$$

where Ω denotes the set of contracts with predicted positive supply (for now, this is only a single contract).
4. To identify the optimal set Ω, loop over the following steps
   a. If Ω already consists of all contracts, exit the loop and proceed to step 5.
   b. Denote by k the contract with the highest value of ψ_{ijt}^r among the contracts that are not in Ω. If $\lambda_{it}^r > \psi_{ikt}^r$ exit the loop and proceed to step 5.
   c. If $\lambda_{it}^r \leq \psi_{ikt}^r$ add contract k to Ω. Update the Lagrange multiplier by using the formula in (11). Continue the loop.
5. For the contracts in Ω, calculate the optimal, predicted supply level as

$$\widehat{L}_{ijt}^r = \widehat{\gamma}_j\left(\left(\frac{\psi_{ijt}^r}{\lambda_{it}^r}\right)^{\frac{1}{1-\hat{\alpha}}} - 1\right). \tag{12}$$

For the other contracts set the optimal supply to 0.

After running the algorithm, we can average the predictions over R draws to obtain estimates of the optimal level of supply for a given farm household and a given choice task.

2.3.2. Supply elasticities

We calculate the median marginal elasticity based on the formula (12). Specifically, for a positive supply level, the elasticity of the supplied land $\widehat{L}_{ijt}^r$ with respect to attribute $\mathbf{X}_{ijt}$ is given by:

[5] In Pinjari and Bhat (2021) these are also adjusted by the price of the given alternative from the budget equation, but in our case all these “prices” are equal to one.

$$e_{ijt} = \frac{\partial \widehat{L}^r_{ijt}}{\partial \mathbf{X}_{ijt}} \frac{\mathbf{X}_{ijt}}{\widehat{L}^r_{ijt}}$$

This calculation is conditional on the farmer supplying a positive amount of land under the given contract, which is a reasonable assumption for calculating elasticities, as the elasticity is not defined when $\widehat{L}^r_{ijt} = 0$.

2.3.3. Welfare measure

In the case of standard discrete choice models as MXL, it is common to calculate welfare measures as a ratio $-\boldsymbol{\beta}_i/\lambda_i$. This is considered to be an estimate of the marginal rate of substitution, as these parameters can be interpreted as marginal utilities. In the case of the MMDCEV, this interpretation is no longer possible, because (5) cannot be considered a utility function. Hence, some other approach is needed to identify a welfare effect. We define $CV_{ijt}(x)$ as the total compensation (WTA) required for a farm household to enroll x% of its arable land in contract j from a zero-payment baseline, holding the contract's non-price attributes and utility level fixed. We compute $CV_{ijt}(x)$ by solving for the payment level that induces the predicted allocation $\widetilde{L}_{ijt} = x\Gamma_i$ under the estimated MMDCEV with a land-based budget. We use the following steps.

1. Predict the optimal supply levels, $\widehat{L}^r_{ijt}$, given no compensation.[6]
2. Calculate the utility level for the predicted optimal consumption levels, using the formula in (6): $\widehat{U}^r_{it} = U(\widehat{\mathbf{L}}^r_{it} | \boldsymbol{\beta}^r_i, \lambda^r_i, \widehat{\alpha}, \widehat{\boldsymbol{\gamma}})$.
3. Set the new supply level for the contract j as $\widetilde{L}^r_{ijt}(x) = \max(\widehat{L}^r_{ijt}, x\Gamma_i)$. Namely, the supply level either stays the same, if the farmer enrolls the given share even without any compensation, or is set to a given share of total land.
4. Keeping the supply level for the contract j fixed at $\widetilde{L}^r_{ijt}(x)$, calculate the optimal supply levels for other contracts. We denote them by $\widetilde{L}^r_{ikt}(x)$. Note that because the utility function in (6) is additive, and the "prices" in the budget equation in (7) are fixed at 1, this can be done by repeating the prediction algorithm that was outlined above, without the alternative j and with a smaller available land, $\widetilde{\Gamma}_i = \Gamma_i - \widetilde{L}^r_{ijt}(x)$.
5. Calculate the compensating variation as

$$CV^r_{ijt}(x) = \frac{1}{\lambda^r_i} \left[\log \left(\frac{\widehat{U}^r_{it} - \sum\limits_{\substack{k=1 \\ k \neq j}}^{J} \frac{\widehat{\gamma}_k}{\widehat{\alpha}} \exp\left(V^r_{ikt}\right) \left[\left(\frac{\widetilde{L}_{ikt}(x)}{\widehat{\gamma}_k} + 1 \right)^{\alpha} - 1 \right]}{\frac{\widehat{\gamma}_j}{\widehat{\alpha}} \left[\left(\frac{\widetilde{L}_{ijt}(x)}{\widehat{\gamma}_j} + 1 \right)^{\alpha} - 1 \right]} \right) - V^r_{ijt} \right]. \tag{13}$$

To obtain an estimate of compensating variation on the individual level, one can average the output of the formula in (13) over R draws. We calculate median compensating variation, which is expected to be more robust to extreme values and can help to avoid exploding values that are common when having price coefficient assumed to follow a log-normal distribution (Hole, 2007; Train and Sonnier 2005; Greene et al., 2005; Train and Weeks, 2005). As a robustness check, we re-estimate the MMDCEV including behavioral covariates (risk, generalized trust, institutional trust, environmental attitudes, and perceptions specific to results-based contracts) to examine how these factors shift baseline utilities; see Appendix A.

3. Study design

In this section, we provide information regarding the survey and the VCE that we implemented to investigate farmer preferences for practice-based and results-based contracts.

3.1. Questionnaire design

The survey was organized around the research question of farmers' choices between results-based and practice-based contracts aimed at promoting biodiversity on arable land. The structure of the survey was as follows.

In the introduction, we extensively explained the differences between the two types of contracts, as well as the farming practices involved. This was interspersed with questions on farmers' knowledge and experience, as well as their attitudes toward the payment mechanisms. Next, the volumetric choice sets were presented. The VCE included in the survey was used to observe farmers' willingness to enroll their arable land into two different types of contracts: results-based and practice-based. These contract types served as two labeled alternatives, in addition to the opt-out (no contract) alternative.

The practice-based biodiversity conservation contract included an ambitious combination of four land-management requirements:

[6] Note that if farmers have positive preferences for certain types of contracts, for example due to their environmental attitudes, they may choose to enroll some share of land even if no compensation is given.

1. Introducing winter cover crops and stubble intercrops (catch crops).
2. Using at least five different main crop types, including the cultivation of legumes, with a minimum share of 10% each.
3. Allocating at least 10% of the enrolled arable land to flowering field margins and crops for winter bird use.
4. Allocating at least 10% of the enrolled arable land to set-aside.

Alternatively, farmers could enroll in the results-based contract, in which payments depended on an expert-measured multi-level biodiversity index. The survey explained various ways in which farm biodiversity could be conserved and how the biodiversity index would be measured (see Fig. 1 for an example of graphical material provided to respondents). The measurement was explained as considering various biodiversity levels and combining them into a single biodiversity index. It was assured that if a farmer who enrolled in a results-based contract implemented the same practices as required by the practice-based contract, their remuneration would be approximately the same.

The advantage of results-based contracts was that achieving higher levels of biodiversity or applying more effective practices would result in larger remuneration or reduced effort, as well as allowing greater flexibility for the same biodiversity and payment levels (Herzon et al., 2018). On the other hand, it was associated with higher risk, as deteriorated biodiversity levels or conservation indicators could result in lower payments. For example, if environmental factors such as extreme weather events or pest infestations led to a decline in the biodiversity indicators measured on the farm, the farmer would receive a lower payment despite their management practices.

A third alternative was an opt-out option that made it possible not to enroll any part of one's land in any of the contracts. The descriptions of the contract types, as presented in the survey, are summarized in Table 1.

Our experiment was deliberately labeled to compare contract mechanisms rather than individual practices. The practice-based alternative was presented as a single, high-ambition bundle of four biodiversity-enhancing requirements (cover crops/stubble intercrops; at least five main crop types including legumes ≥10% each; ≥10% flowering field margins and crops for winter bird use; and ≥10% set-aside). We held these requirements fixed across choice tasks to keep cognitive burden manageable in a multi-country VCE and to ensure comparability of mechanism-specific responses. The results-based alternative left the choice of practices to farmers but tied payments to an expert-measured, multi-level biodiversity index. To ensure comparability of expected payments across mechanisms, respondents were told that implementing the same practices as required by the practice-based contract under a results-based contract would yield approximately the same expected payment.

The other attributes used to describe characteristics of the contracts included collective implementation. From the practitioner perspective, there is an interest in combining results-based and collective contracts because social involvement has been shown to make various policies more effective and policy-relevant (Spangenberg et al., 2015; Schmidt et al., 2020). To take this into account, we included a bonus payment dependent on the biodiversity level of the area surrounding one's farm, measured at the landscape level. This bonus is a combination of collective and results-based approaches and depends on the extent to which neighboring farmers also adopt conservation measures to increase biodiversity on their farms and on how effective such a collective effort is. Such a collective and results-based bonus is particularly well suited for the protection of migratory species, as coordinated actions can lead to more significant environmental benefits than individual efforts (Herzon et al., 2018; Schmidt et al., 2020; Spangenberg et al., 2015).

Identification comes from experimental variation in (i) the mean annual payment per enrolled hectare (practice- and results-based), (ii) the payment range for results-based contracts (±10%, ±25%, ±50%), (iii) the mean landscape-level bonus per hectare (practice- and results-based), and (iv) the bonus range (±10%, ±25%, ±50%). The landscape-level bonus is results-contingent and thus functions as a collective/outcome-based incentive that depends on biodiversity measured in the farm's environs; varying its level and range identifies farmers' willingness to accept such collective, outcome-dependent payments. Our design does not decompose marginal utilities of individual practices within the practice-based bundle nor does it experimentally vary neighbors' adoption rates or the spatial radius of the collective. We therefore interpret the estimated effects as preferences for contract type and for payment schedules (including collective, landscape-level bonuses), not as structural peer-interaction parameters.

The annual payment of each contract was presented per hectare of the land enrolled. For the practice-based contract, it was presented as a fixed amount per hectare, while for the results-based contract, the annual payment was described as an interval to introduce uncertainty over the resulting payment. The amounts of bonus payments for both practice-based and results-based alternatives were also presented as a range of values. These ranges were experimentally varied as 10%, 25%, or 50% below and above the mean (expected) payment. The value ranges and annual payments were determined based on current payments for similar practice-based contracts in the studied countries, as well as through consultations with farm advisors and stakeholders, to ensure the ranges matched the expected WTA of farmers.

In all choice tasks, the contract duration was held constant and not varied across alternatives. The choice tasks were framed as new AECM offered under the 2023 CAP, and payments were expressed per hectare per year. We deliberately did not include duration as an attribute to (i) keep the experimental design parsimonious and the cognitive load manageable in a volumetric (quantity-allocating) setting, and (ii) avoid confounding the comparison of contract types (practice- vs results-based) and payment attributes (annual payment; landscape-level bonus). In the EU context, AECM typically involve multi-year commitments, and the literature consistently finds that longer durations require higher compensation (Schulze et al., 2024). Our design therefore treats duration as fixed at a standard multi-annual horizon while focusing identification on the attributes central to our methodological objectives.

Eliciting stated preferences in terms of WTA presents significant challenges concerning incentive compatibility and truthful preference revelation. Unlike WTP formats, which can be designed to be incentive compatible under certain conditions in DCEs (Carson and Groves, 2007), the incentive compatibility properties of WTA formats are less well understood and more difficult to ensure. This is particularly relevant for VCEs, where the incentive properties have not been thoroughly explored. Despite these

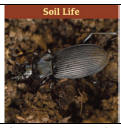
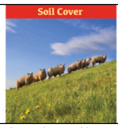
	Soil life	Soil cover	Water, nest and shelter features	Flowering and native plants	Plant structure and composition	Creating corridors for wildlife
						
Ways to conserve	rotating crops, reducing tillage, using cover crops, manure or compost, using cover crops in understory for perennial crop retaining untiled areas, which support ground-nesting insects, reptiles, amphibians, birds, and mammals	keeping the soil covered with plants (crops or other plants, including in under-storey for perennial crop) allowing non-invasive plants to grow along fences, roadways and in ditches leaving undisturbed strips of cover crop when mowing or haying a grassland as refuge for animals	reducing water use by planting crops appropriate for climate, increasing soil organic matter and irrigation efficiency supporting animals with in-field puddled water or small ponds, create brush piles, bee blocks, nest boxes, nest platforms and other suitable shelters and nests for animals	using sequentially flowering or native plants interspersed in crops, in the understory, or at the ends of crop rows retaining at any time, at least part of one field with a flowering crop or cover crop in crop perimeters, and in natural areas on the farm, conserving plants that provide berries and seeds as food	increasing diversity in crop perimeters, and in natural areas on the farm (plants that have stems with hollow centers, retaining snags, downed, decomposing logs, shrubs, wildflowers, grasses and leaf litter) allowing natural habitats to recolonize some patches	connecting natural areas on and off the farm allowing larger animals access through the farm, using wildlife friendly fencing
Ways to measure	soil sampling and analysis: measurement of organic matter	soil sampling and analysis: measurement of erosion, nitrogen absorption, phosphorus status	existence of various habitats and their elements, abundance of selected species	satellite imagery, flower colour index	satellite imagery, structuring degree of agricultural patches	patch diversity index, Shannon diversity index

Fig. 1. Examples of ways in which biodiversity on different levels could be conserved and measured, as presented to farmers.

Table 1
A summary of the descriptions of the contract types as presented in the survey.

Practice-based contract requires the adoption of ALL of the following practices:

1) Introducing winter cover crops and stubble intercrops (catch crops)
2) Using at least five different main crop types, including the cultivation of legumes, with a minimum share of 10% each
3) Allocating at least 10% of the arable land covered by the contract to flowering field margins and winter bird use
4) Allocating at least 10% of arable land covered by the contract to set-aside

Results-based contracts allow farmers to choose ANY practices they want (the survey provided a non-exhaustive list of examples; see the online supplement for the full wording).

- If you implement the same practices as required by practice-based contract, your remuneration will be approximately the same;
- If you implement additional practices, or choose other practices that will be more effective for conserving or increasing biodiversity at your farm, your remuneration will be larger;
- If you implement fewer practices or other practices that will be less effective, your remuneration will be lower.

No contract means no obligations and no additional payments.

challenges, we proceeded with a WTA framework to capture the compensation farmers require to enroll their land into agri-environmental contracts. We addressed potential biases by carefully designing the survey to be as realistic and understandable as possible, including detailed descriptions and visual aids, and pre-testing it with farmers to refine the instrument based on their feedback.

The attributes and their levels are summarized in Table 2.

In each choice set, there were three labeled alternatives (practice-based, results-based, and no contract), and farmers were asked to divide all of their arable land among them. The land allocation question was: "How much arable land would you enroll?" Inputs were non-negative integers ("rounded, without decimals") and were bounded by the respondent's eligible arable area as reported earlier in the questionnaire. The survey interface enforced a hard land-budget constraint so that out-of-range entries and sums exceeding the eligible area could not be submitted. We chose this bounded free-entry format rather than a long list of discrete quantity options to avoid interval censoring and anchoring to pre-listed values, while still keeping the budget constraint salient (cf. discussions of VCE elicitation formats in Carson et al., 2022).[7] This type of question was inspired by the work of Kuhfuss et al. (2016) and later used by Latacz-Lohmann and Breustedt (2019) and Vaissière et al. (2018). An example of the choice card is presented in Fig. 2.

Because the practice-based alternative is presented as a fixed, multi-component bundle, the experiment does not identify marginal utilities for individual practice elements. Likewise, although we vary the landscape-level bonus (mean and range), we do not

[7] Expressing allocations as percentages would require a subsequent conversion to hectares for MMDCEV estimation and welfare metrics (which are per ha by design) and can be error-prone for small farms. Our bounded hectare entry therefore matches both policy units and the land-based budget used in the model, while preserving the continuous nature of the VCE allocation.

Table 2
Attributes and attribute levels used in the discrete choice experiment.

Attributes	Attribute levels
Annual payment (mean)	50, 75, 100, 125, 150, 175, 200, 225, 250, 275, 300 EUR[a]
Annual payment (variation)	Practice-based contract: 0 (fixed)
	Results-based contract: ±10%, ±25%, ±50%[b]
Bonus payment (mean)	10, 20, 30, 40, 50, 60 EUR
Bonus payment (variation)	±10%, ±25%, ±50%

Notes: The practice bundle (four management requirements) is fixed across choice tasks by design. Identification relies on randomized variation in mean annual payment (both mechanisms), payment range (results-based only: ±10%, ±25%, ±50%), mean collective/landscape bonus (both mechanisms), and bonus range (±10%, ±25%, ±50%).

[a] Payments were presented in national currencies using PPP-corrected exchange rates.

[b] Used to produce a range around the mean.

	Practice-based contract	**Results-based contract**	**No contract**
Annual payment per ha of arable land enrolled in the contract	200 EUR (fixed if practices are implemented)	150 – 250 EUR (depending on measured biodiversity level)	0 EUR
Bonus payment depending on the biodiversity of the farm's environs **(annually, per ha of arable land enrolled)**	45 – 75 EUR (depending on the measured biodiversity level of the area surrounding your farm)	30 – 50 EUR (depending on the measured biodiversity level of area surrounding your farm)	0 EUR
How much arable land would you enroll?	____ ha	____ ha	____ ha

Fig. 2. Example of a choice card (translation).

experimentally vary neighbors' behavior or the spatial scope of the "collective." As a result, our estimates capture preferences for a landscape-level, outcome-contingent incentive rather than structural peer effects.

Each farmer was presented with 12 choice cards. The design included 48 choice tasks, which were blocked into 4 sets of 12. Choices could refer to the respondent's owned and/or leased land. The experimental design was optimized to maximize Bayesian D-efficiency of the MNL model (Scarpa and Rose, 2008), with country-specific priors adjusted after the pilot study and twice during the implementation of the main survey.

The experiment was followed by debriefing questions regarding farmers' motivations and perceptions of contract design features, including several risk constructs that plausibly moderate preferences for contract type. We use these variables in Appendix A as interactions that shift the alternatives' baseline utilities. The survey ended with a battery of socio-demographic and farm characteristics questions.

The survey was developed with the help of 11 group consultations that included researchers and policymakers. The VCE was based on an extensive literature review summarized by Schulze et al. (2024). To ensure comprehension of the survey and validity of the VCE study, we conducted qualitative in-depth interviews with 4–6 farmers in each country at various stages of survey development.[8]

3.2. *Survey administration and sample*

The study was conducted between January and August 2022 in four countries: Germany (421 farmer participants), the Netherlands (512), Poland (804), and Czechia (98), with a total sample of 1835 respondents. A professional market research company recruited

[8] The survey's full translation into English, along with German, Dutch, Polish, and Czech language versions, data, estimation software codes and detailed results are presented in an online supplement to this paper, available at http://czaj.org/research/supplementary-materials.

farmers from major general panels of respondents in Germany, the Netherlands, and Poland. In Czechia, the survey was distributed in early 2022 via a mass email to approximately 2,000 members of the Association of Private Farming of the Czech Republic (Asociace soukromého zemědělství ČR) that distributed an online questionnaire among its all members. Only individuals who stated that they actively participate in managerial decisions on farms and own or lease at least one hectare of arable land were allowed access to the computer-assisted web interview (CAWI). In Table 3, we present the breakdown of the ownership structure of farms in our sample. As can be seen, the majority of farms that we analyze are family-owned, followed by the individually-owned estates. A comprehensive sample description is provided in Appendix B. The online supplement to this paper presents a copy of the survey instrument.

4. Results

In this section, we report the results of our analysis. First, in Section 4.1, we present the qualitative analysis of farmers' choices in VCE. Then, in Sections 4.2–4.5, we present a rigorous comparison of the results from MMDCEV and MXL models. Specifically, we compare coefficient estimates, supply predictions, supply elasticities, and, finally, welfare measures.

4.1. VCE data

The VCE data provides additional insights over standard DCE only if respondents indicate positive quantities of the analyzed good for at least two alternatives. In this subsection, we examine farmers' choices and investigate their propensity to enroll their land into more than a single contract.

In Table 4, we present how often farmers chose a given number of alternatives. Overall, we observe that in about 61.1% of choices, respondents chose a single alternative. We find that only 24.2% of those single-alternative choices correspond to the "no contract" option. This indicates that in the majority of cases, choices correspond to farmers selecting a single type of agri-environmental contract. As our VCE setting involves labeled alternatives, a large share of individuals choosing a single alternative may be influenced by the labeling effect, which can strengthen preferences for a particular contract type due to its explicit identification. Nonetheless, we observe that in 22.7% of cases, farmers indicated two alternatives. Again, only about 20.1% of these choices involve a "no contract" option, which means there is a significant portion of choices in which farmers enrolled parts of their land into both practice-based and results-based contracts. Finally, about 16.2% of choices involved all three alternatives.

When we break down these shares by country of origin, we find that farmers in the Netherlands are generally the most likely to choose more than a single alternative, whereas farmers from Poland are the least likely to do so (Table 4). This heterogeneity across countries could be driven by several factors, such as differences in preferences for a given type of contract or variations in the amount of available land. Regarding the latter, in Fig. 3 we investigate the correlation between available land and the propensity to enroll land into a given number of contracts. We find that individuals with more land are generally more likely to indicate more than a single contract. Since, on average, Polish farmers in our sample have much less land than farmers in other countries, this could partly explain the heterogeneity observed in Table 4.

4.2. Comparison of models' coefficients

In Table 5, we report the estimates of the MMDCEV and MXL models. As dependent variables differ between them (multiple-continuous vs. discrete), the value of the likelihood function or information criteria cannot be really compared between the two. Furthermore, MMDCEV involves the estimation of an additional four coefficients that define the profile of the utility function. In both cases, we find that the mixed version provides a significant improvement over a standard MDCEV and MNL models.[9] Of course, when estimating mixed model it is crucial to choose a proper mixing distributions for random parameters. In what follows, we assume normal distribution for alternative-specific constants (ASCs) and variation attributes, as it led to better fit than using a distribution that can only take positive/negative values. For payment attributes we use a mu-shifted log-normal distribution (Crastes dit Sourd, 2024) that is defined on positive axis.[10] All random parameters are fully correlated, but for brevity sake we do not report the full covariance matrix, and only provide the estimates of the standard deviations.

The estimates of the means of the random parameters in the MMDCEV indicate that, on average, individuals prefer practice-based contracts over results-based contracts. Still, the significant and positive ASC for results-based contracts indicates that farmers prefer them compared with no contract at all. The annual and bonus payments attributes are assumed to follow a mu-shifted log-normal distribution, which forces random parameters to be strictly positive. As this specification led to a better fit than the model with these parameters having a normal distribution, we treat this as evidence that farmers prefer receiving larger compensation. Furthermore, these coefficients are not significantly different from each other on average, which means that for farmers, obtaining 1 EUR more from the annual payment is equivalent to obtaining 1 EUR more from the bonus payment. On average, the variation attributes are not significant for either type of payment. Since most farmers believed that they would need to put extra effort into environmental action under results-based contracts and would likely receive higher payments, it is possible that a larger maximum payment may serve as an

[9] LR statistic equals to 16288.2 for MNL vs. MXL comparison (p-value < 0.0001) and 28431.2 for MDCEV vs. MMDCEV comparison (p-value $<$ 0.0001).

[10] Likelihood function of MMDCEV model with all random parameters having a normal distribution is equal to −57,376.88, whereas using mu-shifted distribution for the payment attributes improves it to −56,948.99. It also provides an improvement over a standard log-normal distribution.

Table 3
The structure of ownership of the land in the analyzed sample.

	Share of respondents	Median size of the farm (ha)
Owned by family (you own the farm together with other members of your household, e.g. wife/husband, parents, other family members living together and sharing a budget)	41.58%	4
Owned by me as the sole owner	36.51%	7
Owned in partnership with other farmers / Company	7.30%	7
Owned by a corporation / Agricultural enterprise	5.50%	10
Owned by a cooperative	3.38%	18
Owned by other people (leased)	3.22%	5
State-owned (leased)	1.74%	5

Table 4
Shares of choices in which farmers enrolled some of their land into a given number of alternatives (contracts).

	Single alternative	Two alternatives	Three alternatives
Overall	61.07%	22.73%	16.20%
CZE	67.94%	20.92%	11.14%
DE	57.92%	23.59%	18.49%
NL	44.42%	27.36%	28.22%
PL	72.48%	19.56%	7.96%

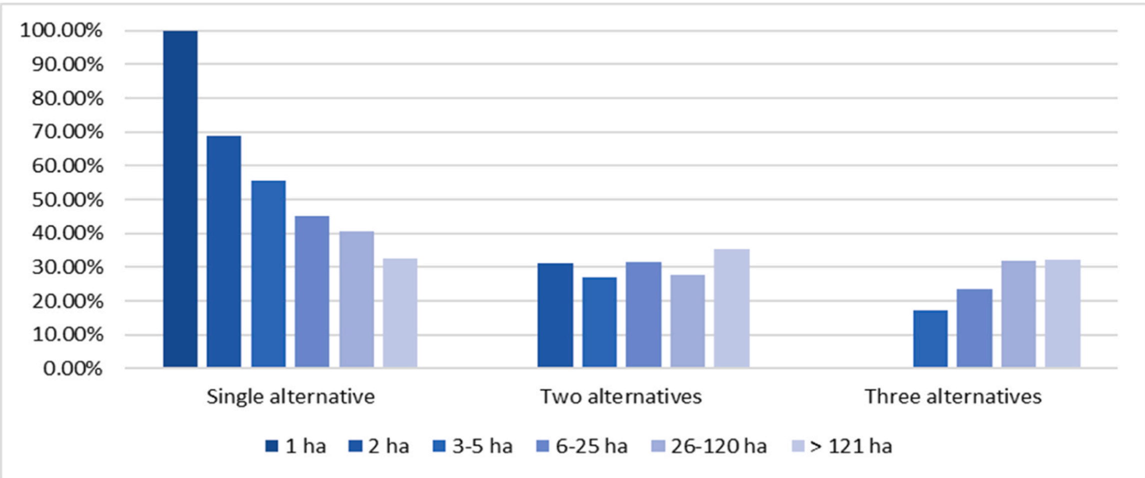


Fig. 3. Shares of choices in which farmers enrolled some of their land into a given number of alternatives as a function of available land.

encouraging factor for some farmers. However, a lower minimum payment may be a discouraging factor for others, making the effect of the variation of payments ambiguous and, on average, not significant. Nonetheless, the significant standard deviations of the random parameters for these attributes indicate considerable heterogeneity in how farmers perceive these attributes.

Comparing the coefficients between the two models, we can observe remarkable similarities. Indeed, all coefficients have the same level of significance and are of the same level of magnitude. Even though these estimates are so similar, they have a different interpretation. In the MXL we can say that on average, farmers have a 1.553 higher utility from enrolling into a practice-based contract than not enrolling into any contract at all. This is not true for the MMDCEV, as these coefficients do not represent marginal utilities. As such, it is difficult to interpret this similarity. As explained by Bhat (2008), when individuals choose to consume only a single alternative, the MDCEV model collapses to the regular multinomial logit model.[11] As already mentioned, we observe that in 61.1% of choices, farmers would indicate only a single contract (see Table 4). We would expect that the remaining 38.9% of choices would reveal some additional information about farmers' preferences that would lead to better estimates of the parameters. However, at least for $\boldsymbol{\beta}_i$ and λ_i, this does not seem to be the case.

For the MMDCEV model, we estimate additional α and γ parameters, which describe the shape of the utility function specified in Eq. (2). We obtain an estimate of α equal to −0.155, which is significantly less than 0; a value of 0 would correspond to a logarithmic

[11] In our case, MMDCEV collapses to MXL.

Table 5
Results of the MMDCEV and MXL models.

		Mixed MDCEV model				MXL model			
	Dist.	**Means**		**Std. Dev.**		**Means**		**Std. Dev.**	
Practice-based contract (ASC)	N	1.135	***	5.664	***	1.553	***	4.873	***
		[0.189]		[0.153]		[0.167]		[0.188]	
Results-based contract (ASC)	N	0.366	**	5.444	***	0.402	**	4.981	***
		[0.180]		[0.144]		[0.174]		[0.223]	
Annual payment (100 EUR)	mu-LN	-2.865	***	2.828	***	-2.706	***	2.716	***
		[0.104]		[0.072]		[0.136]		[0.119]	
Annual payment variation	N	-0.1		0.59	***	0.073		1.134	**
		[0.107]		[0.153]		[0.197]		[0.496]	
Bonus payment (100 EUR)	mu-LN	-3.397	***	3.019	***	-2.788	***	2.531	***
		[0.263]		[0.105]		[0.413]		[0.195]	
Bonus payment variation	N	0.048		0.311	***	-0.03		0.712	***
		[0.058]		[0.085]		[0.092]		[0.253]	
		Coefficients of the utility profile (MMDCEV only)							
Alpha: common for all contracts		-0.155	***						
		[0.016]							
Gamma: Practice-based contract		2.718	***						
		[0.103]							
Gamma: Results-based contract		2.816	***						
		[0.104]							
Gamma: No contract		4.482	***						
		[0.222]							
		Model diagnostics							
LL at convergence		-56948.99				-14559.64			
AIC/N		5.175				1.325			
BIC/N		5.187				1.335			
N*T (observations)		22020				22020			
N (respondents)		1835				1835			
K (parameters)		31				27			

Notes: (i) Random parameters follow either a normal distribution (N) or mu-shifted log-normal distribution (mu-LN); (ii) For the mu-LN distribution coefficients correspond to the parameters of the underlying normal distribution; (iii) Standard errors are reported in square brackets; (iv) *** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level

specification. However, we note that in our specification, α is confounded with the scale coefficient (which was normalized to 1), so we cannot readily interpret its magnitude. On the other hand, the γ parameters are very similar between the practice-based and results-based contracts, with values of about 2.7, whereas it is much higher for the "no contract" alternative. A higher value of γ implies a lower marginal utility, even if the baseline utility, $\exp(V_{ijt})$, is the same for different contracts.

Estimates from an augmented specification that includes behavioral covariates are reported in Appendix A. Several of these covariates are statistically significant and improve model fit, indicating that risk attitudes, trust in experts/EU, and pro-environmental orientations help explain the heterogeneity observed in baseline utilities across contract types. The majority of the coefficients' signs and magnitudes are in line with expectations and do not alter the main findings.

4.3. Comparison of supply predictions

In Table 6, we compare mean supply predictions for MMDCEV and MXL models. For the former, these are calculated using the procedure outlined in Section 2.3.1. They are calculated for each choice task and individual in the sample and then averaged. For MXL, we calculate the farmers' supply using formulas in (4). Specifically, we translate choice probabilities into individuals' supply by either assuming that farmers choose the contract that has the highest probability of being chosen and then enroll their whole land into this contract ("*single contract*"), or that farmers enroll their land into each contract relatively to the predicted probabilities ("*probability based*").

As expected, results reported in Table 6 show that practice-based contracts are characterized by the highest supply. This is the most pronounced for the "*single contract*" MXL. Furthermore, predictions from the "*single contract*" MXL indicate that no farmer would actually choose the "*no contract*" option. In contrast, MXL "*probability based*" predictions are very similar to the MMDCEV ones. When comparing the mean absolute errors, we can see that MXL "*single contract*" has generally the highest error, whereas the other two approaches are very similar to each other.

The similarity between MMDCEV predictions and "*probability based*" MXL is further confirmed when we plot the predicted supply as a function of the total land that farmers have available (Γ_i).[12] This is presented in Fig. 4 for practice-based contracts. Only the "*single contract*" MXL provides a different forecast, as it basically predicts that all land will always be allocated to the practice-based contract.

[12] This was done only for practice-based contracts as an example, the plots for the other two alternatives lead to the same conclusions.

Table 6
Comparison of mean predictions of the supply from MMDCEV and MXL models.

	Mean prediction			Mean absolute error		
	MMDCEV	MXL (single contract)	MXL (probability based)	MMDCEV	MXL (single contract)	MXL (probability based)
Practice-based	40.674	83.980	45.543	27.219	47.810	28.030
Results-based	27.700	9.251	24.115	23.632	29.574	23.497
No contract	24.857	0.000	23.574	25.783	21.593	25.460

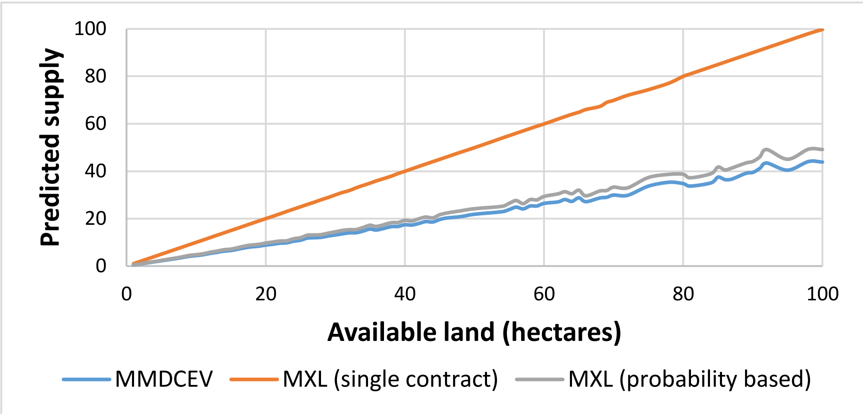


Fig. 4. Predicted supply for the practice-based contracts as a function of the total land that farmers have available.

In contrast, the other two approaches lead to very similar predictions, which seem to be (approximately) a linear function of the available land.

In Fig. 5, we further compare the supply predictions by looking at their distribution in the analyzed sample. To make it more comparable across farmers, we normalize the predictions by the total available land. We dropped a "*single contract*" MXL forecast here, as it would always predict either 0 or 1, so it is not very interesting to look at. When comparing the obtained distributions, two differences seem apparent. First, the MXL seems to predict a wider interval of supply for the practice-based contracts, while at the same time predicting a narrower interval for the results-based contracts. For example, for the practice-based contracts, predictions' distribution seems to drop to almost 0 at 0.55 for MMDCEV, whereas for MXL it continues beyond that. Second, the predictions from MMDCEV are much smoother. It, therefore, seems that by recognizing a continuous dimension of the farmers' choice, MMDCEV is able to provide a better representation of the supply distribution, with better predictions of the extremes and a smoother representation. Still, when looking at the average (cf. Table 6), there seems to be very little difference between the two approaches.

4.4. Comparison of supply elasticities

As the coefficients reported in Table 5 cannot be directly compared across the models, we calculate supply elasticities to further compare the two approaches. For the MMDCEV model, the elasticity is calculated as described in Section 2.3.2. For the MXL model this is a standard elasticity of choice probabilities. The results are reported in Table 7.

As could be expected, the elasticities for variation attributes are not significant, given that their coefficients were, on average, not significant. For the annual payment attribute, based on the MMDCEV model, we observe the elasticities of 0.86 and 1.441 for the practice- and results-based contracts, respectively. In comparison, MXL indicates higher elasticity for the practice-based contracts and lower for the results-based ones. We note, however, that the 95% confidence intervals of these estimates overlap, indicating that these differences may not be significant.

For the bonus payment attribute, based on the MMDCEV model, we observe the elasticities of 0.175 and 0.326 for the practice- and results-based contracts, respectively. In both cases, estimates based on the MXL model are lower, although, again, the difference is likely not significant.

4.5. Comparison of welfare measures

The main appeal of the MMDCEV model is that it internalizes the discrete-continuous character of the VCE data in a manner consistent with a standard microeconomic theory. This allows us to estimate welfare measures that are usually not considered when analyzing standard DCE data. Given that the objective of the stated preference survey was to evaluate farmers' preferences for different types of contracts, it is natural to inquire how much compensation a farmer would require to enroll more land into them. Specifically,

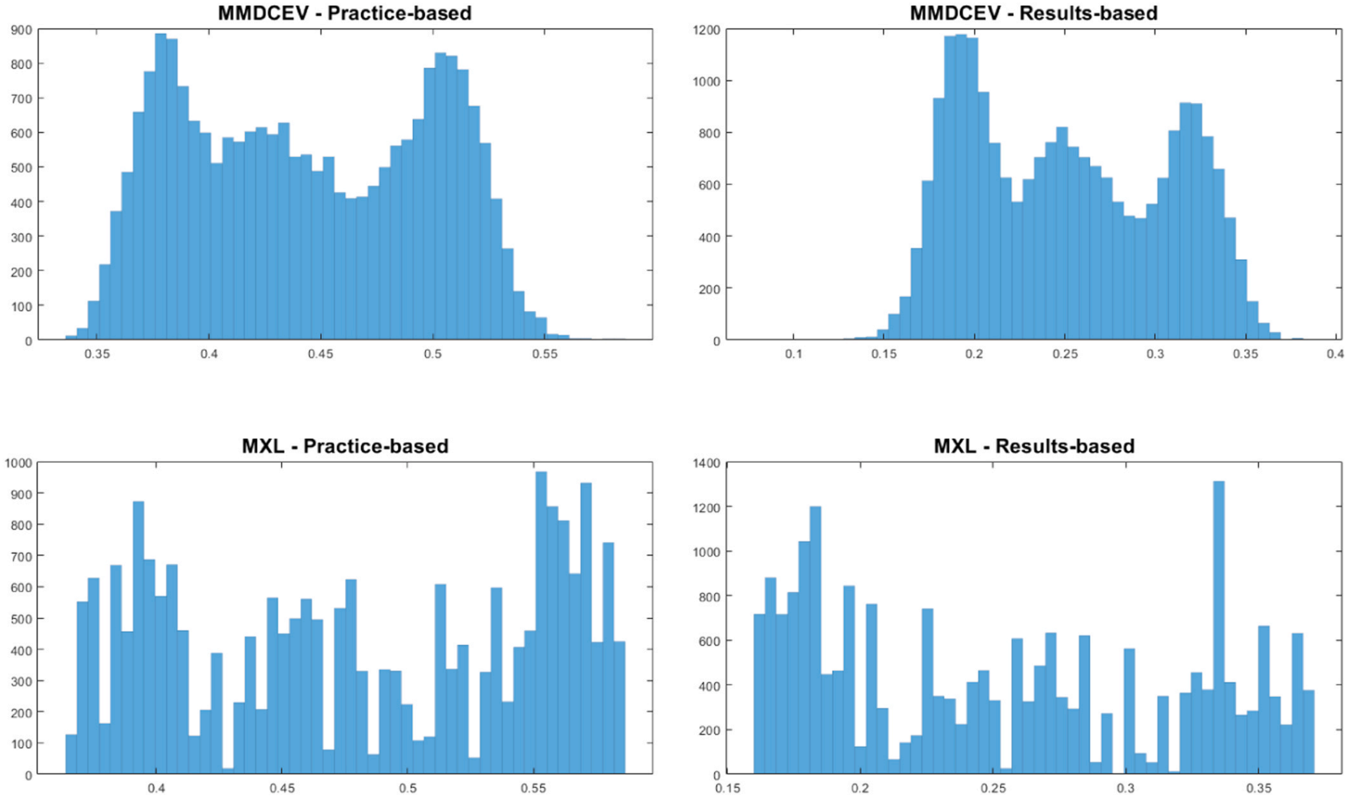


Fig. 5. Comparison of the distribution of predicted supply normalized by the total available land.

Table 7
Marginal elasticities of supply for MMDCEV and MXL models.

	MMDCEV		MXL	
	Practice-based	Results-based	Practice-based	Results-based
Annual payment	0.86***	1.441***	1.202***	1.158***
	[0.089]	[0.098]	[0.226]	[0.150]
Annual payment variation		-0.026		0.008
		[0.032]		[0.046]
Bonus payment	0.175***	0.326***	0.142***	0.234***
	[0.025]	[0.033]	[0.029]	[0.047]
Bonus payment variation	0.007	0.011	0.004	-0.005
	[0.012]	[0.019]	[0.012]	[0.020]

Notes: (i) Standard errors are reported in square brackets (calculated with the Krinsky and Robb simulation procedure); (ii) *** Significant at the 1% level.

the compensating variation (CV), introduced in Subsection 2.3.3, measures the minimal payment needed for a farmer to enroll a given portion of their land into a given contract, while keeping their utility level constant. Such a measure is useful from a policy perspective, as it provides direct information regarding the necessary level of compensation. In Fig. 6, we present these estimates as a function of the share of enrolled land. For example, the median CV for enrolling 50% of the land into a practice-based contract is 102 EUR, whereas it is 556 EUR for the results-based contracts. For 100% land enrollment, the values are 286 EUR and 901 EUR, respectively. From Fig. 6, it seems that the relationship between the share of land and median CV is approximately linear. Surprisingly, for the results-based contracts, even for very small shares, the CV exceeds 300 EUR and seems to never drop to zero.

In Table 8, we compare the CV measure calculated for 100% land enrollment with a standard WTA measure derived from the MXL model. We note that the MXL-based WTA cannot be directly compared with the CV, as the two have different interpretations. Specifically, the CV measure captures the compensation per hectare required for the median farmer to enroll 100% of their land in a given contract. By contrast, the interpretation of WTA is more complex because the MXL model does not account for the amount of land enrolled, despite payments being specified on a per-hectare basis. The estimated WTA reflects the median per-hectare payment required for farmers to prefer entering a given contract type rather than opting out. From a policy perspective, this measure informs the level of per-hectare payments that may be necessary to induce contract uptake, but it cannot be directly translated into enrolled area or total program costs without additional assumptions about land participation. In contrast, the median CV can be readily used for policy analysis, as it explicitly conditions on a targeted enrollment share. Nevertheless, comparing the two measures remains informative. Specifically, we observe stark differences between the two approaches. The positive ASCs for both contracts in the MXL model (see Table 5) indicate that farmers derive positive utility from contract participation. Consequently, no compensation is required to induce enrollment, resulting in negative median WTA estimates. In contrast, positive ASCs in the MMDCEV model do not imply that farmers would voluntarily enroll all of their land in a given contract, which leads to positive CV estimates.

Table 8 also reports several robustness checks assessing whether these patterns hold under alternative distributional assumptions and sample specifications. Overall, the results are highly consistent: CV estimates are positive, with compensation for the results-based contract always exceeding that for the practice-based contract, while WTA estimates are negative. The only exceptions occur in MXL specifications where (i) all parameters are fixed (i.e., an MNL model) and (ii) the analysis is restricted to the DE sample; in these cases, the WTA for the results-based contract is positive. However, the MNL model performs worse than the MXL model across multiple goodness-of-fit measures, and both WTA estimates for the DE sample are statistically insignificant at the 5% level. Finally, we note that welfare measures for the NL sample are implausibly large and therefore not suitable for policy use. Importantly, as shown in the final row of Table 8, excluding the NL sample has little effect on the welfare estimates reported for our main model.

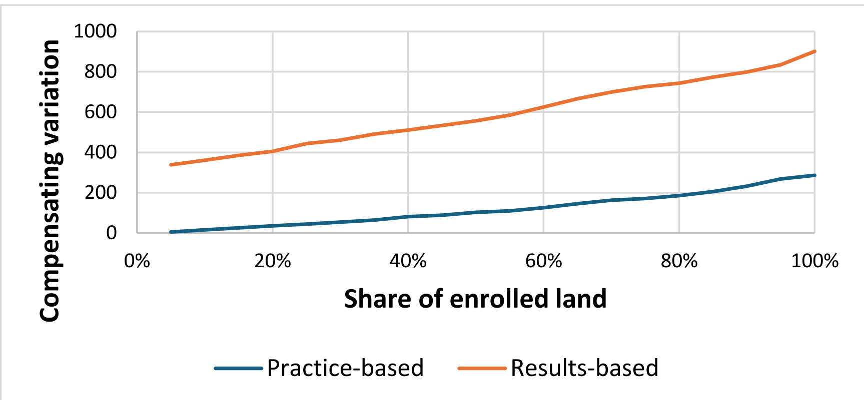


Fig. 6. Median compensating variation based on the MMDCEV model as a function of the share of land enrolled into a given contract.

Table 8
Median compensating variation for the 100% enrollment based on the MMDCEV model and median WTA based on the MXL model.

	MMDCEV (CV)		MXL (WTA)	
	Practice-based	Results-based	Practice-based	Results-based
Main model (full-sample, mu-shifted log-normal distribution)	286.11	901.16	-335.68	-42.52
	[224.76, 357.43]	[737.10, 1080.40]	[-494.17, −216.48]	[-100.77, −2.54]
	Robustness check - different distributional assumptions for the monetary attribute			
Log-normal distribution	277.39	827.3	-298.59	-43.91
	[225.92, 330.85]	[688.79, 998.87]	[-424.92, −200.5]	[-97.66, −4.36]
Fixed	177.99	443.78	-352.78	-144.52
	[147.95, 202.53]	[410.66, 470.63]	[-417.81, −293.90]	[-207.90, −84.68]
Fixed (all parameters)	154.35	358.68	-79.31	155.62
	[139.84, 167.48]	[333.98, 388.08]	[-108.41, −50.22]	[129.75, 181.50]
WTA-space			-549.36	-323.21
			[-600.83. −497.90]	[-364.38, −282.05]
	Robustness check - country-specific models			
PL sample only	80.65	448.88	-375.41	-156.05
	[45.32, 119.39]	[349.23, 571.31]	[-572.24, −226.90]	[-284.14, −54.28]
DE sample only	613.21	1107.76	-148.98	72.45
	[462.29, 801.10]	[824.52, 1449.99]	[-486.94, 2.08]	[-18.23, 250.13]
NL sample only	5401.28	19994.44	-76225.22	-28123.9
	[364.97, 88222.35]	[924.80, 506321.59]	[-458888.69, −1832.68]	[-151160.22, −902.52]
	Robustness check - NL sample excluded			
	248.49	831.43	-286.08	-28.96
	[187.34, 312.17]	[677.38, 997.12]	[-410.92, −188.38]	[-74.79, 0.76]

Notes: (i) 95% confidence intervals are reported in square brackets (calculated with the Krinsky and Robb simulation procedure) (ii) WTA-space is reported only for the MXL model, as such specification does not have a useful interpretation in the MMDCEV model. (iii) CZE was omitted from the country-specific models due to lower sample size. (iv) In Appendix C we provide analogous table with mean CV and WTA, instead of median.

Table 8 contrasts two welfare objects that are often treated similarly in practice but answer different policy questions in our context. The CV measure is an intensive-margin object: it gives the per-hectare annual payment required for the median farmer to enroll a targeted share of land (here: 100%) in a given contract, relative to a zero-payment baseline while holding non-monetary attributes fixed. By construction, this measure can be mapped directly into payment schedules needed to achieve targeted enrollment shares and thus into program-cost calculations.

The MXL-based WTA, by contrast, is a discrete-choice (participation) object: it identifies the per-hectare payment that makes the farmer prefer entering a given contract type rather than opting out, but the MXL model abstracts from the amount of land enrolled. Translating MXL-based WTA into expected enrolled area or total cost therefore requires additional assumptions about the allocation decision (e.g., full vs. partial enrollment conditional on participation).

The comparison nonetheless remains informative. In the MXL model, positive ASCs imply positive utility from participation, which can yield negative median WTA values even when full enrollment would not occur at zero payment. In contrast, in the MMDCEV model, positive baseline utility does not imply that a farmer would voluntarily allocate all land to a contract; the model explicitly reconciles the participation and allocation margins under the land constraint. This is why CV estimates remain positive and increase with the targeted enrollment share. Importantly, the qualitative gap between the two approaches persists across the robustness checks reported in Table 8.

5. Summary and conclusions

VCEs are an emerging method for eliciting individual preferences that have gained popularity and can offer theoretical advantages over DCEs in some settings (Carson et al., 2022). While VCE can sometimes provide a more accurate representation of the decision process, it can be challenging to design, implement, and interpret the results. In the context of farmers' preferences for agri-environmental contracts, VCE is an appealing alternative, as researchers often use a combination of DCE with a follow-up question asking farmers how much land they would enroll into a chosen contract (e.g., Tanaka et al., 2022). VCE provides a clear advantage over such an approach as it allows for unified inference. Additionally, it enables the identification of instances in which a farmer would like to enroll different parts of their land into different contracts. On the other hand, using VCE data requires the estimation of more complex models such as the Mixed Multiple Discrete-Continuous Extreme Value (MMDCEV) model. In this study, we illustrate how this model can be used on VCE data to study farmers' choices and rigorously compare it against a standard DCE data analyzed with the MXL model.

The main challenge regarding operationalizing the MMDCEV model for the case of farmers' choices is that they usually involve some compensation (subsidy) rather than a price (tax). As such, the hypothetical scenario in VCE has a WTA format rather than WTP. This creates an issue because the MMDCEV is usually formulated using an income-based budget equation, which becomes non-binding in this case. We show that one can estimate the model with a land-based budget equation, which avoids this pitfall. This approach fits into a broader literature of using multiple discrete continuous models in settings that do not involve an income-based budget equation.

Probably the most related is the freight transport literature. For example, Tapia et al. (2020) used the MDCEV model to analyze firms' preferences regarding the shipment of 3'000 tons of soy. As freight companies do not have a budget constraint similar to the consumer's choice, Tapia et al. (2020) utilize a percentage-based approach in which firms allocate a percentage of their shipments to different freight options. Such an approach differs from the current application, as the farmers in our study made allocations in absolute terms rather than relative terms. As different farmers operate on lands of different sizes, we believe that using an absolute constraint is more fitting in our case. The land-based budget explicitly reflects the policy instrument (payments per hectare) and preserves the role of land heterogeneity that we document empirically. A formal, side-by-side empirical comparison of level- versus share-based normalizations in the AECM context is an interesting direction for future research.

We propose an algorithm to calculate compensating variation based on the proposed specification of the MMDCEV model. The estimated value informs how much a farmer would have to be compensated to enroll a given percentage of their land to a given contract, so that his utility level would stay at the same level. We find that for practice-based contracts this value ranges from 5.2 EUR for 5% enrollment, up to 286.1 EUR for the 100% enrollment. In contrast, for results-based contracts the values are significantly higher, starting from 338.2 EUR for 5% enrollment and increasing to 913 EUR for 100% enrollment.

The comparison between MMDCEV model estimated on VCE data and MXL model estimated on DCE data revealed many similarities. Specifically, coefficients' estimates as well as supply elasticities are very close in magnitude. However, MMDCEV seems to better represent the distribution of the predicted supply, as it is smoother and tapers off to zero in the tails (cf. Fig. 5). The biggest difference between the two approaches arises when comparing the inferred welfare measures. MMDCEV predicts large compensations that would be necessary to incentivize farmers to enroll their land into AECM. In contrast, WTA values calculated based on the MXL model are negative indicating that no compensation is actually necessary. As such, even though the estimates of ASCs are very similar between the two models, the difference in their interpretation have large consequences for the implied welfare effects. In MMDCEV model, positive signs of ASCs for practice- and results-based contracts are not sufficient to lead to full enrollment, and as such, some compensation may be still necessary. On the other hand, for the MXL-based welfare measure, only negative estimates of ASCs could lead to positive WTA measures.

The context of our study is rooted in the ongoing efforts to align agricultural practices with environmental sustainability goals, particularly within the framework of the European Union's Common Agricultural Policy (CAP). As the CAP evolves, understanding the preferences and motivations of farmers becomes crucial in designing agri-environmental contracts that are both appealing and effective in promoting conservation practices. Our focus on comparing results-based and practice-based contracts through the lens of VCE methodology sheds light on the complex decision-making landscape that farmers navigate when considering participation in these programs.

Despite the novel insights provided by this study into farmers' preferences for agri-environmental contracts, there are several limitations that warrant consideration. First, our empirical findings are based on stated preferences, which, while informative, may not always align with actual behavior. The hypothetical nature of the scenarios presented in VCE might lead to discrepancies between the expressed preferences and the choices farmers would make in real-life situations. This gap between stated and revealed preferences highlights the need for further research that incorporates observational data or experiments designed to validate the predictive accuracy of the models used, especially in the context of unknown incentive properties (Carson and Groves, 2007; Vossler et al., 2012). We acknowledge that the lack of established incentive compatibility for WTA in VCE is a limitation of our study, and the results should be interpreted with this consideration in mind. Future research is needed to explore the incentive compatibility properties of VCEs in a WTA context, potentially developing methodologies to enhance truthful preference revelation in such settings. Furthermore, the reliance on VCE, while innovative, also introduces complexities in both the design and interpretation of the findings. The proposed compensation variation measure requires specification of a base scenario, which in the current study was defined as a zero payment contracts. This was possible because attributes such as land-management requirements were not varied in the design. In the future work, with more complex designs of VCE, calculation of the compensation variation measure would need a careful consideration. We also note that our study did not vary contract duration, even though duration is one of the most influential AECM design features and longer commitments typically attenuate enrollment (Schulze et al., 2024). This was a conscious choice to preserve focus on the VCE-MMDCEV framework, the WTA/land-budget formulation, and the contrast between practice- and results-based contract structures. Future research could integrate duration – and potentially termination ("opt-out") options – into VCEs to study how time horizon interacts with outcome risk, monitoring credibility, and collective (landscape-level) incentives in continuous land-allocation decisions. Finally, we acknowledge that because the collective bonus is tied to measured landscape-level biodiversity, the estimated effect should be interpreted as willingness to accept an outcome-based, landscape-level incentive – a policy lever that can harness coordination benefits – rather than as a direct estimate of social or peer influence.

Concluding this study, we want to highlight the difficulty related to the implementation of results-based contracts in practice. On the one hand, they provide a number of advantages when compared to practice-based contracts. These include a stronger incentive to select land where the greatest improvement relative to the baseline is possible, a clearer link between payment and biodiversity achievement, greater management flexibility, and the utilization of farmers' knowledge and professional judgment (Herzon et al., 2018). On the other hand, the results of the current study indicate that results-based contracts would require much higher compensation. As such, it is necessary to evaluate whether the benefits of results-based contracts warrant the additional payment. Future research should also investigate in more detail the causes of farmers' lower preferences for this type of contract. Possibly, farmers are risk-averse with respect to how their efforts will be evaluated by biodiversity experts, or it is an effect of lower familiarity with these types of contracts (see Appendix A, for some evidence of such effects).

For future research, it would be interesting to explore different ways of accommodating the WTA format of the farmers' choice in the MMDCEV model. One possibility would be to additionally elicit the expected cost of implementing a given contract. Then the budget equation could be established given that the sum of costs minus the sum of subsidies should not exceed the farm's profit. This is unfortunately not possible in the current study as expected costs were not collected. Furthermore, future work could also evaluate some novel formulations of the MMDCEV model that can be found in Bhat et al. (2015), Bhat (2018), and Bhat (2022).

CRediT authorship contribution statement

Lenny van Bussel: Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Milan Ščasný:** Writing – review & editing, Resources, Project administration, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization. **Christoph Schulze:** Writing – review & editing, Supervision, Methodology, Investigation, Data curation, Conceptualization. **Olimpia Markiewicz:** Writing – review & editing, Project administration, Methodology, Conceptualization. **Solen Le Clec'h:** Writing – review & editing, Supervision, Conceptualization. **Wojciech Zawadzki:** Writing – review & editing, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Czajkowski Mikolaj:** Writing – review & editing, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Katarzyna Zagórska:** Writing – review & editing, Project administration, Methodology, Investigation, Conceptualization. **Wiktor Budziński:** Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Julian Sagebiel:** Writing – review & editing, Methodology, Conceptualization. **Jens Rommel:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization. **Matěj Opatrný:** Writing – review & editing, Resources, Methodology, Data curation, Conceptualization. **Bettina Matzdorf:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Models with additional covariates

In this Appendix, we augment the baseline models with individual-level attitudinal and belief covariates that theory suggests are salient for the relative attractiveness of practice- vs results-based contracts. We document measurement and coding of these variables in Table A1 and then report the coefficient estimates for MMDCEV and MXL models in Table A2.

Table A1
Description of selected attitudinal variables utilized in the augmented models

Name in the model	Description	Mean				Transformation
		PL	CZE	DE	NL	
Risk attitude	How do you see yourself: are you generally a person who is fully prepared to take risks or do you try to avoid taking risks? (0:10; 0-not at all willing to take risks, 10-very willing to take risks)	5.4	5.6	5.9	7.0	Continuous; Divided by 10
Results-based contracts more risky	Please tell us which type of contract do you consider more risky (1–7; 1-Definitely practice-based contract, 7 -Definitely results-based contract)	4.6	5.3	4.4	4.9	Binary; = 1 if 5 or more
Trusts EU	Please indicate, to what extent you trust or do not trust the European Union. (1–5; 1-Do not trust at all, 5 -Trust a lot)	2.9	2.7	2.8	3.4	Binary; = 1 if 4 or more
Trusts agricultural experts	Please indicate, to what extent you trust or do not trust the agricultural experts. (1–5; 1-Do not trust at all, 5 -Trust a lot; mean)	3.0	3.6	3.2	3.7	Binary; = 1 if 4 or more
Environmental issues important	Environmental issues are important to me personally (1–5; 1-Strongly disagree, 5 -Strongly agree)	3.8	4.2	3.8	4.0	Binary; = 1 if 4 or more
Farm management has impact on environment	The way I manage my farm has an impact on the condition of the natural environment (1–5; 1-Strongly disagree, 5 -Strongly agree)	3.8	4.4	3.8	3.9	Binary; = 1 if 4 or more
Willing to change practices	I would be willing to change practices and farm management to promote environmental protection (1–5; 1-Strongly disagree, 5 -Strongly agree)	3.6	3.9	3.7	3.9	Binary; = 1 if 4 or more
Farmer is best expert	The farmer is the best expert on the environmental issues of his farm (1–5; 1-Strongly disagree, 5 -Strongly agree)	3.6	3.9	3.8	3.8	Binary; = 1 if 4 or more

In the augmented specifications, covariates enter the models as interactions with ASCs to capture the preference heterogeneity related to the type of contract. As reported in Table A1, most covariates were measured using a Likert scale, but they were transformed into binary variables for ease of interpretation. Everything else in the specifications of these models remained the same as in the models reported in the main text. We acknowledge that, given the attitudinal nature of these variables, the model may suffer from measurement error. The survey design does not permit modeling them as latent constructs within a hybrid choice framework, and developing a hybrid version of the MMDCEV model is beyond the scope of this study. As such, these variables should be treated as proxies for underlying attitudes, and the estimated effects should be interpreted as associations rather than casual impacts.

Table A2
Results of the MMDCEV and MXL models with additional covariates

		Mixed MDCEV model				**MXL model**			
	Dist.	**Means**		**Std. Dev.**		**Means**		**Std. Dev.**	
Practice-based contract (ASC)	N	-1.622	***	6.860	***	-0.817	**	4.642	***
		[0.310]		[0.123]		[0.414]		[0.172]	
Results- based contract (ASC)	N	-2.365	***	6.366	***	-2.102	***	4.704	***
		[0.278]		[0.127]		[0.429]		[0.188]	
Annual payment (100 EUR)	mu-LN	-2.942	***	2.480	***	-2.700	***	2.702	***
		[0.083]		[0.059]		[0.130]		[0.107]	
Annual payment variation	N	-0.025		0.785	***	0.059		1.041	***
		[0.103]		[0.147]		[0.181]		[0.388]	
Bonus payment (100 EUR)	mu-LN	-3.752	***	2.839	***	-2.988	***	2.682	***
		[0.563]		[0.250]		[0.427]		[0.187]	
Bonus payment variation	N	0.054		0.356	***	-0.034		0.658	***
		[0.056]		[0.116]		[0.087]		[0.223]	
		Practice-based contract (interaction)		**Results-based contract (interaction)**		**Practice-based contract (interaction)**		**Results-based contract (interaction)**	
Risk attitude		3.302	***	4.257	***	1.950	***	2.709	***
		[0.387]		[0.345]		[0.610]		[0.630]	
Results-based contracts more risky		0.760	***	0.095		1.243	***	0.768	***
		[0.144]		[0.130]		[0.266]		[0.272]	
Trusts EU		2.492	***	2.217	***	0.464		0.301	
		[0.208]		[0.185]		[0.297]		[0.304]	
Trusts agricultural experts		-0.417	**	-0.126		0.139		0.427	
		[0.164]		[0.151]		[0.276]		[0.282]	
Environmental issues important		-1.742	***	-1.213	***	0.043		-0.112	
		[0.257]		[0.226]		[0.348]		[0.357]	
Farm management has impact on environment		-0.398	*	-1.086	***	-0.041		-0.057	
		[0.230]		[0.205]		[0.334]		[0.342]	
Willing to change practices		1.394	***	1.552	***	1.157	***	1.369	***
		[0.169]		[0.168]		[0.311]		[0.320]	
Farmer is best expert		0.737	***	0.440	***	-0.682	**	-0.927	***
		[0.141]		[0.127]		[0.297]		[0.305]	
		Coefficients of the utility profile							
Alpha: common for all contracts		-0.120	***						
		[0.004]							
Gamma: Practice-based contract		2.696	***						
		[0.059]							
Gamma: Results-based contract		2.781	***						
		[0.059]							
Gamma: No contract		4.308	***						
		[0.080]							

Notes: (i) Random parameters follow either a normal distribution (N) or mu-shifted log-normal distribution (mu-LN); (ii) For the mu-LN distribution coefficients correspond to the parameters of the underlying normal distribution; (iii) Standard errors are reported in square brackets; (iv) *** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level

The extended MMDCEV model reveals several consistent patterns that align with economic intuition and the qualitative feedback gathered during survey pre-testing. We find a strong effect of risk preferences, with farmers who self-assessed as more risk-taking being more likely to enroll land into agri-environmental contracts. At the same time, farmers who perceive results-based contracts as more risky are more likely to enroll land in practice-based contracts. As expected, trust also plays a significant role in shaping farmers' choices. Specifically, farmers who trust the EU are more likely to enroll in these contracts. Finally, farmers who stated that they would be willing to change their practices to improve the environment are more likely to enroll their land in both types of contracts. At the same time, several estimated effects are less intuitive. For example, farmers who trust agricultural experts have lower utility from a practice-based contract. We would rather expect an increased enrollment in results-based contracts, as these farmers should be less skeptical about biodiversity measurements. We also observe that pro-environmental attitudes, as measured by '*Environmental issues important*' and '*Farm management has impact on environment*' variables, have a negative effect. Again, we would rather expect the opposite effect. Finally, we observe that farmers who believe that farmers are the best experts regarding the environment on their land are more likely to enroll in both types of contracts. In this case, we would expect a stronger effect for results-based contracts as these farmers should have a higher expected return from such agreements.

When comparing the results with the MXL model, we observe much stronger differences than in the model without interactions reported in the main text. Again, it seems that although the two approaches are rather similar when looking at the averages, they exhibit somewhat different properties upon more detailed analysis. Specifically, in the MXL model, we observe that environmental and trust-related attitudes are not significant. Furthermore, the interactions with the '*Farmer is best expert*' covariate have opposite signs to the MMDCEV model. This divergence may be caused by the fact that in the MXL model, the interactions are only used to explain a discrete choice part of the farmers' decision process. In contrast, in the MMDCEV, they also explain the continuous dimension, namely, how much land a farmer will enroll in a chosen contract. To better understand this difference, one could also add these covariates into the utility profile coefficients of the MMDCEV to try to differentiate between the effect of these covariates on different dimensions of the choice process. However, such analysis is beyond the scope of this study. Our core methodological contribution – and the central focus of this paper – concerns the use of VCE data within an MMDCEV framework tailored to subsidy-driven WTA contexts. For this reason, and to keep the exposition parsimonious, we report the attitudinally augmented models here in the appendix as a robustness check. These results complement rather than alter the substantive conclusions of the main analysis.

Appendix B. Sample profile and attitudinal measures

Table B1
Sample description by country

Measure	PL	CZE	DE	NL
Male (%)	33.7	85.7	73.6	62.3
Age (years, mean)	39.4	48.0	44.3	36.6
Household size (mean)	3.9	4.1	3.4	3.4
Higher education (%)	38.8	63.3	40.4	33.4
Secondary education (%)	43.9	29.6	7.8	34.2
Vocational (%)	13.3	7.1	32.3	25.2
Elementary+agri course (%)	1.6	0.0	15.7	6.2
Elementary / lower secondary (%)	2.4	0.0	3.8	1.0
Full-time farmer (%)	21.5	83.7	49.4	62.5
Part-time with other income (%)	26.2	12.2	25.2	18.9
Part-time without other income (%)	10.9	2.0	10.0	11.9
Hobby farmer (%)	37.8	1.0	12.6	6.1
Hours/week among part-time (mean)	19.9	28.0	23.9	25.7
Farm income 100% (%)	9.3	39.8	10.5	20.1
Farm income 75–100% (%)	9.5	21.4	25.4	28.9
Farm income 50–75% (%)	13.2	16.3	25.9	30.3
Farm income 25–50% (%)	13.7	15.3	17.1	13.9
Farm income 0–25% (%)	32.3	3.1	18.1	4.1
Total agricultural area (ha, mean)	47.6	529.4	545.6	839.3
Arable land (ha, mean)	19.1	387.2	169.3	316.4
Arable farm (%)	70.0	35.7	50.1	49.4
Livestock farm (%)	10.1	28.6	24.5	27.5
Mixed farm (%)	19.9	35.7	25.4	23.0
AES: currently participating (%)	8.7	78.6	39.2	38.3
AES: participated in the past (%)	8.7	5.1	19.7	32.4
AES: never, but considered (%)	25.1	6.1	19.7	19.1
AES: never, and do not plan (%)	26.5	2.0	11.4	3.5
AES: not eligible (%)	16.0	2.0	5.7	3.7
General risk willingness (0–10; mean)	5.4	5.6	5.9	7.0
Monitoring reliability (1–7; mean)	4.3	3.0	4.3	5.1
Would implement more practices under results-based (1–7; mean)	4.3	3.8	4.5	5.1
Would expect higher payment under results-based (1–7; mean)	4.7	5.3	5.0	5.1
Generalized trust: "most people can be trusted" (%)	25.2	29.6	39.4	50.8
Trust in neighbors (1–5; mean)	3.2	3.7	3.5	3.6
Trust in the EU (1–5; mean)	2.9	2.7	2.8	3.4
Trust in agricultural experts (1–5; mean)	3.0	3.6	3.2	3.7
Environmental issues are important (1–5; mean)	3.8	4.2	3.8	4.0
Willing to change practices for environment (1–5; mean)	3.6	3.9	3.7	3.9
Belief that results monitoring would be fair (1–5; mean)	3.4	2.9	3.4	3.6

Appendix C. Comparison of mean welfare measures

In this Appendix, we replicate the results reported in Table 8 using mean welfare measures instead of medians. As expected, welfare estimates are generally higher when based on the mean; however, the overall conclusions remain consistent with those obtained using the median. The main difference is that the mu-shifted log-normal distribution employed in the main model yields substantially lower welfare estimates than the standard log-normal distribution. Under the latter, the resulting welfare measures are implausibly large. We view this contrast as evidence supporting the robustness and suitability of the distributional assumption adopted in the main model.

Table C1
Mean compensating variation for the 100% enrollment based on the MMDCEV model and mean WTA based on the MXL model

	MMDCEV (CV)		MXL (WTA)	
	Practice-based	**Results-based**	**Practice-based**	**Results-based**
Main model (full-sample, mu-shifted log-normal distribution)	1783.69 [1466.53, 2158.82]	2467.81 [2017.02, 2994.83]	-1336.82 [-1911.87, −900.25]	-387.09 [-738.07, −87.51]
	Robustness check - different distributional assumptions for the monetary attribute			
Log-normal distribution	14961.77 [9178.64, 26214.12]	22610.76 [13306.74, 39262.91]	-15548.28 [-31943.23, −6902.57]	-3770.4 [-9341.61, −78.43]
Fixed	460.37 [433.15, 487.39]	607.78 [575.60, 638.21]	-352.73 [-417.76, −293.85]	-143.66 [-206.97, −83.85]
Fixed (all parameters)	365.41 [341.60, 389.63]	500.24 [466.86, 535.41]	-79.31 [-108.41, −50.22]	155.62 [129.75, 181.50]
WTA-space			-549.36 [-600.83, −497.90]	-323.21 [-364.38, −282.05]
	Robustness check - country-specific models			
PL sample only	1141.94 [881.97, 1449.80]	1490.22 [1170.39, 1888.81]	-1027.38 [-1503.13, −655.37]	-547.14 [-912.41, −229.85]
DE sample only	2374.71 [1684.76, 3330.94]	2939.86 [2074.12, 4116.00]	-1472.31 [-4196.91, −133.30]	166.76 [-1177.18, 1615.09]
NL sample only	50688.16 [1617.03, 2168777.71]	85939.55 [2495.88, 3958114.44]	-213655.08 [-1333465.56, −3043.61]	-134449.87 [-823294.90, −1772.67]
	Robustness check - NL sample excluded			
	1622.75 [1305.97, 1998.97]	2243.65 [1833.10, 2746.71]	-1144.9 [-1592.08, −778.38]	-280.8 [-561.51, −12.18]

Notes: (i) 95% confidence intervals are reported in square brackets (calculated with the Krinsky and Robb simulation procedure) (ii) WTA-space is reported only for the MXL model, as such specification does not have a useful interpretation in the MMDCEV model. (iii) CZE was omitted from the country-specific models due to lower sample size.

Data availability

Data will be made available on request.

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