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Economic valuation of ecosystem services: a natural capital approach to agri-food production systems

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“Study and, in general, the pursuit of truth and beauty are areas of activity in which we are allowed to remain children throughout our lives”

— Albert Einstein

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Abstract

Extensive research has focused on the economic valuation of ecosystem services and on the development of policy instruments to incorporate natural capital into agri-food systems, consistent with the System of Environmental Economic Accounting—Ecosystem Accounting framework. This thesis addresses these themes through a series of interconnected studies. A meta-analysis of 116 papers reporting 368 valuation estimates shows that an econometric model controlling for (a) the geographical and socio-economic characteristics of study sites, (b) the valuation methods and beneficiary types, and (c) the biophysical and ecological attributes of the relevant biomes and ecosystem services explains 50.2% of the variation in reported values. The analysis indicates that the only statistically significant driver in methodological terms is the application of non-market valuation approaches. While monetary values are a mix of market and non-market values, most economic value of natural capital is outside the market and can only be captured by non-market valuation techniques. Subsequent discrete choice experiments with Italian winegrowers, estimated using nonlinear random-parameter logit models, reveal that risk preferences, probability weighting, and prior adoption experiences significantly influence willingness to accept payments for sustainable practices. At the same time, the weak integration of natural capital assets into farm-level risk assessments suggests that policy incentives aimed at fostering long-term resilience and resource conservation may fail to elicit the intended behavioral responses when farmers do not perceive environmental improvements as economically salient within the relevant time horizon. A further choice experiment with consumers, analyzed through a latent class model incorporating a control-function approach to address the endogeneity of attitudinal scales, uncovers heterogeneous preferences for food labels associated with ecosystem service provision. The level of informational detail, and its interaction with organic certification, strongly influences willingness to pay. Finally, a simulated exchange-value approach is employed to translate the indirect

and non-use values of biodiversity related ecosystem services derived from non-market valuation techniques into accounting consistent asset values for urban parks. Taken together, the findings identify the determinants of ecosystem service valuation across stakeholder groups, quantify the economic incentives required to encourage the adoption of sustainable practices, and develop a transferable methodology to aligning welfare based valuation with national accounting standards. The thesis thereby offers an evidence base for designing cost-effective agri-environmental policies and market-based conservation instruments.

Abstract (in italiano)

Un'ampia letteratura si è concentrata sulla valutazione economica dei servizi ecosistemici e sullo sviluppo di strumenti di policy volti a integrare il capitale naturale nei sistemi agroalimentari, in coerenza con il quadro del System of Environmental Economic Accounting – Ecosystem Accounting. La presente tesi affronta tali tematiche attraverso una serie di studi tra loro interconnessi. Una meta-analisi di 116 contributi scientifici, che riportano complessivamente 368 stime di valore, mostra che un modello econometrico in grado di controllare per (a) le caratteristiche geografiche e socio-economiche dei siti di studio, (b) i metodi di valutazione e le tipologie di beneficiari, e (c) gli attributi biofisici ed ecologici dei biomi e dei servizi ecosistemici considerati, spiega il 50,2% della variazione nei valori riportati. L'analisi evidenzia che, dal punto di vista metodologico, l'unico determinante statisticamente significativo è l'applicazione di approcci di valutazione non di mercato. Sebbene i valori monetari osservati comprendano una combinazione di valori di mercato e non di mercato, la maggior parte del valore economico del capitale naturale risiede al di fuori del mercato e può essere colta esclusivamente mediante tecniche di valutazione non di mercato. Successivi esperimenti di scelta discreta condotti con viticoltori italiani, stimati mediante modelli logit non lineari a parametri casuali, rivelano che le preferenze rispetto al rischio, la ponderazione delle probabilità e le esperienze pregresse di adozione influenzano in modo significativo la disponibilità ad accettare compensazioni per l'adozione di pratiche sostenibili. Al contempo, la debole integrazione delle risorse di capitale naturale nelle valutazioni del rischio a livello aziendale suggerisce che gli incentivi di policy volti a promuovere la resilienza di lungo periodo e la conservazione delle risorse potrebbero non generare le risposte comportamentali attese qualora gli agricoltori non percepiscano i miglioramenti ambientali come economicamente rilevanti nell'orizzonte temporale considerato. Un ulteriore esperimento di scelta con i consumatori, analizzato mediante un modello a classi latenti che incorpora un approccio di

control function per affrontare l'endogeneità delle scale attitudinali, mette in luce preferenze eterogenee per le etichette alimentari associate alla fornitura di servizi ecosistemici. Il livello di dettaglio informativo, nonché la sua interazione con la certificazione biologica, influenza in modo marcato la disponibilità a pagare. Infine, viene adottato un approccio basato sul valore di scambio simulato per tradurre i valori indiretti e di non uso dei servizi ecosistemici legati alla biodiversità, derivati da tecniche di valutazione non di mercato, in valori patrimoniali coerenti con i principi contabili applicabili ai parchi urbani. Nel loro insieme, i risultati individuano i determinanti della valutazione dei servizi ecosistemici tra diversi gruppi di portatori di interesse, quantificano gli incentivi economici necessari a favorire l'adozione di pratiche sostenibili e sviluppano una metodologia trasferibile per allineare la valutazione del benessere con gli standard della contabilità nazionale. La tesi fornisce pertanto una solida base empirica per la progettazione di politiche agro-ambientali efficienti in termini di costo e di strumenti di conservazione basati sul mercato.

Contents

Introduction **10**

1 The Economic Value of Ecosystem Services: Meta-analysis and Potential Application of Value Transfer for Freshwater Ecosystem **16**
1.1 Introduction . . . 17
1.2 Systematic Literature Review . . . 20
1.3 Meta-regression Model for the Monetary Value of ES and post-estimation Diagnostics . . . 22
1.4 Data Standardization . . . 29
1.5 Potential meta-analytic Value Transfer Application . . . 30
1.6 Preliminary Descriptive Results . . . 31
1.7 Meta-regression Model post-estimation Diagnostics and Results . . . 37
1.8 Potential Application of Meta-analytic Value Function . . . 41
1.9 Conclusion . . . 43

2 Understanding Winegrowers' Adoption of Sustainable Practices in Eco-Schemes: Risk Attitudes and Perceptual Conditioning of the Probability of Impact on Net Returns **45**
2.1 Introduction . . . 46
2.2 Background and Theory . . . 49
2.2.1 Adoption of sustainable practices for the provision of ecosystem services and incentive-based programs . . . 49
2.2.2 Market-based incentives and private monitoring . . . 51
2.2.3 Modeling risk attitudes towards changes in net returns . . . 52
2.3 Method and Data . . . 54
2.3.1 Survey Implementation and Data . . . 54
2.3.2 Choice Experiment Design . . . 57
2.3.3 Modeling Choices Under Uncertainty and Risk Preferences . . . 60
2.3.4 Empirical Model and Marginal Willingness to Accept Estimation . . . 62
2.4 Results . . . 65
2.4.1 Perceptual conditioning and risk attitude toward net income fluctuation 66
2.4.2 Market-based programs and private monitoring system . . . 69
2.4.3 Payments for adopting sustainable practices in the vineyard . . . 72
2.5 Conclusions . . . 75

3 Asset Integration and Risk Attitudes: Further Evidence from a Choice Experiment on the Adoption of Sustainable Agricultural Practices **78**
3.1 Introduction . . . 79
3.2 Background and Theory . . . 81
3.2.1 Asset Integration and the Argument of the Utility Function . . . 81
3.2.2 Stochastic Net Returns and the Role of Risk Preferences . . . 82

3.2.3 Probability Weighting and Calibration Critiques . . . 83
3.3 Method and Data . . . 84
3.3.1 Survey Implementation and Data . . . 84
3.3.2 Choice Experiment Design . . . 86
3.3.3 Choices Under Uncertainty and Asset Integration . . . 89
3.3.4 Empirical Approach . . . 92
3.4 Results . . . 93
3.5 Discussion and Conclusions . . . 97

4 Ecosystem Services in Food Labels: the Role of Different Information Layers in Shaping Consumers Preferences 99
4.1 Introduction . . . 100
4.2 Literature Review . . . 102
4.3 Materials and Method . . . 104
4.3.1 Data and Survey Design . . . 104
4.3.2 Experimental Design . . . 106
4.3.3 Choice Tasks and Treatment Design . . . 109
4.3.4 Econometric Approach . . . 110
4.3.5 Empirical Model . . . 114
4.4 Results . . . 116
4.4.1 Descriptive Analysis . . . 116
4.4.2 Estimation Results . . . 121
4.5 Discussion and Conclusions . . . 128

5 Indirect and Non-use Benefits of Biodiversity in System of National Accounts: a Discrete Choice Experiment and Integration into a Simulated Exchange Value Approach 132
5.1 Introduction . . . 133
5.2 Literature review . . . 136
5.3 Material and methods . . . 137
5.3.1 Survey and Discrete Choice Experiment Design . . . 137
5.3.2 Econometric Approach . . . 140
5.3.3 Transitional Stock Dependence . . . 142
5.3.4 Simulated Exchange Value . . . 144
5.4 Results . . . 146
5.4.1 Descriptive analysis . . . 146
5.4.2 Latent Class Model estimation . . . 149
5.4.3 WTP and Simulated Exchange Value Estimations . . . 152
5.5 Discussion and Conclusions . . . 157

Conclusions 159

List of Tables

1 Main economic evaluation methods of ES provided by freshwater ecosystems 21
2 Summary statistics of explanatory variables 25
3 Mean monetary value for each biome related to the specific ES (Int$2020 $ha^{-1}year^{-1}$) 34
4 Economic evaluation methods used, and relative weight of the specific ES valuated 35
5 Mean ES monetary values according to applied valuation method (Int$2020 ha^{-1} $year^{-1}$) 36
6 Meta-regression model results 37
7 Wineries Characteristics 55
8 Adoption of sustainable practices in the past 5 years, adoption through incentive-based programs and percentage of area involved 56
9 Characteristics of the contract for adopting sustainable practices 58
10 Random Parameters Logit results for different probability weights 67
11 Mean Willingness to Accept (WTA) for Program Attributes in (,000 €/ha) Across Models Estimated Using Different Probability Weights 71
12 Wineries Characteristics 85
13 Characteristics of the contract for adopting sustainable practices 87
14 Random Parameters Logit Results for Different Wealth Indicators 95
15 Attributes and Levels Considered in the Choice Experiment 107
16 Sociodemographic variables and balance tests 117
17 Attitudinal questions and relative frequency (%) (1 = only slightly concerned; 7 = extremely concerned) 118
18 Prior and objective knowledge regarding four food-related labels and ES. . . . 120
19 Exploratory factor analysis 122
20 Estimation of the LCM with indicator 123
21 Estimation of WTP values 125
22 Attributes, Levels, Descriptions, and Information on Interventions used in the Discrete Choice Experiment 139
23 Descriptive Statistics 147
24 Attitudinal questions and relative frequency of the score (1 = strongly disagree; 5 = strongly agree) 148
25 Exploratory Factor Analysis 150
26 Estimation of the Latent Class Model with indicator 151
27 Stock Dependent Observed Marginal Willingness-to-Pay Estimates 153
28 Exchange Prices, Exchange Values and Asset Values for one square meter of current ES stock 155

List of Figures

1 Observed and predicted freshwater ecosystem value, ranked in ascending order for observed values. 42
2 Deviation from the linear specification of the probability weighting function at the mean, maximum, and minimum values of γ and τ. 68
3 Distributions of risk attitude parameters and risk premium 69
4 Distribution of conditional willingness to accept (WTA) estimates for sustainable practices. WTA estimates are based on individual specific parameter means 74

Introduction

In recent decades, food systems have been optimized to secure national food supplies under tight cost constraints and rising global demand. This has driven a shift toward increased waste, more meat-intensive diets, and large-scale industrial agriculture, contributing to power imbalances across the value chain (FAO, 2023). As a result, contemporary food systems have become increasingly exposed to a wide range of risks that threaten both corporate performance and broader environmental and social outcomes (European Environment Agency, 2024).

Recent estimates of the "hidden costs" associated with unsustainable and unhealthy agri-food systems place these externalities at USD 12.7 trillion in 2020, nearly 10% of global GDP, and exceeding the sector's own economic contribution (FAO, 2023). This suggests that prevailing practices may ultimately destroy more value than they create.

The unsustainable relationship between global food systems and nature is evident in their heavy dependence on natural capital, particularly within the agricultural production stage, which relies almost entirely on natural ecosystems for its continued viability. Food production is a major driver of environmental degradation, including greenhouse gas emissions, freshwater withdrawals, eutrophication, land-use change, and biodiversity loss (IPBES, 2024). These dependencies and impacts create material risks for investment portfolios exposed to agrifood value chains, but they also open opportunities to support more sustainable production models.

The effective management of Natural-capital-related risks depends on improved access to high-quality and decision-relevant data (European Environment Agency, 2024).

Natural capital accounting represents a critical mechanism for supporting long-term resilience and more sustainable food production across the value chain (United Nations, 2025).

This research is part of the ongoing transformation of statistical and economic systems, which are shifting from a measurement framework centered exclusively on market production

of goods and services toward a broader representation of wealth that explicitly incorporates natural capital and ecosystem services (ES) (Stiglitz, 2015; Dasgupta, 2021; United Nations, 2025). Conventional macroeconomic indicators, as GDP, are increasingly recognized as insufficient to capture economic progress in the context of environmental degradation, biodiversity loss, and the depletion of natural resources (Stiglitz et al., 2010; Pörtner et al., 2022; NGFS-INSPIRE Study Group on Biodiversity and Financial Stability, 2022). The erosion of natural capital undermines the sustainability of human and produced capital accumulation, as substitutability between natural and other forms of capital is limited and context-dependent (Dasgupta, 2021; Turner et al., 2019). International debates on the economics of nature have emphasized that the biosphere constitutes a fundamental form of capital, underpinning the capacity of economic systems to generate income over time, while being subject to critical thresholds and potentially irreversible changes (Costanza et al., 1997; Stiglitz, 2013).

The concept of natural capital provides a bridge between ecology and economics, interpreting ecosystems as assets that, through biophysical processes, generate flows of services essential for production and human well-being (Barbier, 2019; Boyd and Banzhaf, 2007). Biodiversity, encompassing genetic, species, and ecosystem diversity, functions as an "enabling asset" that enhances productivity, resilience, and stability of ecological systems, thereby strengthening their capacity to deliver services over time (Mace et al., 2012; Baumgärtner and Quaas, 2010). The degradation and simplification of ecosystems, particularly within agricultural landscapes, diminish their ability to supply regulating, supporting, and cultural services, increasing vulnerability to climatic, sanitary, and market shocks (Díaz et al., 2015).

The international statistical community has responded to these challenges through the development of the System of Environmental Economic Accounting – Ecosystem Accounting (SEEA EA), which provides a standardized framework for measuring ecosystem extent, condition, service flows, and monetary value in a manner consistent with national accounting principles (United Nations, 2025). The SEEA EA framework comprises five main accounting

structures: (i) ecosystem extent accounts, (ii) ecosystem condition accounts, (iii) physical and (iv) monetary accounts of ES flows, and (v) ecosystem asset accounts based on exchange values (United Nations, 2025). This approach enables the derivation of adjusted income and wealth measures, reflecting ecosystem degradation or enhancement, and supports informed environmental and economic policy design (Obst et al., 2016; Keith et al., 2017).

National strategies for natural capital accounting increasingly adopt SEEA-aligned methodologies to integrate ecological information into routine policy and economic decision-making. For example, the United States has proposed a system of "Statistics for Environmental–Economic Decisions," encompassing ecosystem, soil, water, biodiversity, and other natural asset accounts fully compatible with national accounts (The White House, 2023). The rationale is simultaneously macroeconomic, financial, and regulatory: understanding dependencies and risks associated with natural capital loss is essential for financial stability, fiscal policy assessment, and firm competitiveness (Dasgupta, 2021). Similarly, the European Commission adopted the technical proposal to amend Regulation 691/2011 on European environmental economic accounts to include the evaluation of ecosystems and biodiversity (EU Commission, 2022).

As Dasgupta (2021) argues, Natural capital depletion largely results from negative externalities and incomplete property rights affecting common-pool resources. Terrestrial and marine ecosystems, species, and functional ecological processes are often subject to open-access or inadequately defined ownership regimes, preventing the internalization of environmental costs of production and consumption and leading to overexploitation and degradation (Ostrom, 1990).

A central challenge in ecosystem accounting lies in translating service flows into monetary magnitudes compatible with conventional economic statistics. SEEA EA prescribes the use of actual or imputed exchange values consistent with national accounts, while recognizing that such values typically underestimate the total social value, which includes consumer surplus,

indirect-use, and non-use values (United Nations, 2025). Developing conceptual and methodological bridges between accounting values and welfare values, alongside spatially explicit benefit-transfer methods, is crucial to enhancing the informational and policy relevance of ecological accounts (Johnston et al., 2021; Navrud and Strand, 2018).

Agri-food systems are at the intersection of economic and ecological interactions, accounting for a substantial share of global emissions, biodiversity pressures, and land and water use, while also functioning as potential providers of key ES (Díaz et al., 2015; FAO, 2024). Agricultural landscapes, when sustainably managed, contribute to habitat conservation, hydrological regulation, carbon sequestration, erosion control, pollination, and cultural services, generating both private and public benefits (Power, 2010). However, these systems are also highly exposed to multiple sources of risk, including climatic variability, price volatility, and pest or disease outbreaks, which can amplify the consequences of natural capital degradation on farm incomes and ES provision.

Policy interventions targeting agri-food systems often operate under conditions of high uncertainty, where both ecological and socio-economic responses are difficult to predict. To address these challenges, governments and international organizations deploy a combination of "soft" instruments, such as payments for ecosystem services, agro-environmental schemes, voluntary certification programs, and labeling initiatives, alongside regulatory and market-based instruments (Pe'Er et al., 2022; Runge et al., 2022). These mechanisms aim to align private incentives with the social value of ES, internalizing externalities, and mitigating systemic risks associated with ecosystem degradation. Importantly, the effectiveness of these instruments depends not only on economic incentives but also on farmers' risk attitudes, farm-level asset portfolios, and information availability, as well as consumers' perceptions and willingness to pay (WTP) for environmentally friendly products (Hasler et al., 2022; Carlsson et al., 2022).

From a financial stability perspective, the loss of natural capital generates physical, tran-

sition, and liability risks for firms and financial intermediaries, which can propagate through supply chains and markets, potentially resulting in systemic effects (Dasgupta, 2021). In the agricultural sector, these risks manifest as yield shocks, price volatility, asset devaluation, and exposure to evolving regulatory requirements on biodiversity, land use, and emissions. Policy and market instruments that account for risk and uncertainty, therefore, play a critical role in ensuring long-term resilience of agricultural production while safeguarding ES (Just and Just, 2016).

Against this backdrop, this thesis contributes to methodological and empirical research enabling the integration of ES and biodiversity values into accounting systems and agri-food policy design. Specifically, it addresses four complementary fronts: (i) a meta-analytic review of monetary valuations of ES, to understand the determinants of economic valuation to date (Johnston et al., 2018; Navrud and Strand, 2018); (ii) an investigation of farmers' decisions regarding instruments that internalize environmental effects, introducing business risk and asset structures in terms of natural capital; (iii) an investigation of information schemes that influence consumers' WTP for ES-related product characteristics, as a component of private external financing for natural capital conservation; and (iv) the development of methods to translate indirect and non-use values, typical of non-market valuations of biodiversity, into simulated exchange values consistent with accounting principles (Caparrós et al., 2003, 2017).

The thesis is structured around five empirical and methodological studies. Chapter 1 presents a meta-analysis of freshwater ES valuations, estimating meta-analytic value-transfer functions suitable for SEEA applications. Chapters 2 and 3 analyze farmers' adoption of sustainable agricultural practices under incentive schemes, with Chapter 2 focusing on risk perceptions and contractual design, and Chapter 3 on asset integration and farm-level wealth structures in terms of natural capital. Chapter 4 examines consumer preferences for ES-informed food labels, assessing the effects of informational layers and trust in shaping WTP. Chapter 5 addresses indirect and non-use biodiversity benefits, applying a simulated exchange-

value approach to derive asset-compatible monetary values aligned with SEEA EA.

The originality of this thesis lies in integrating three often-separated domains, monetary valuation of ES, incentive-based agri-environmental policies, and consumer communication on ES provision—within a coherent SEEA-aligned framework (United Nations, 2025). By combining meta-analysis, discrete choice experiments, risk-based modeling, and simulated exchange-value procedures, the research provides operational tools and empirical evidence to bridge the gap between theoretical valuation of ES and their practical integration into accounting and policy frameworks (The White House, 2023). This approach contributes to the broader international agenda of reorienting economic measurement, financial regulation, and policy design in light of natural capital constraints and the essential role of biodiversity in ensuring long-term human well-being (Dasgupta, 2021).

Ultimately, the thesis seeks to support the development of resilient, sustainable agri-food systems through methodologies that integrate economic valuation, risk-sensitive decision-making, and policy instruments. By providing insights into how natural capital and ES can be systematically incorporated into accounting frameworks, the work informs both micro-level management decisions and macro-level policy strategies, advancing the goal of sustainable development under uncertainty.

1 The Economic Value of Ecosystem Services: Meta-analysis and Potential Application of Value Transfer for Freshwater Ecosystem

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Abstract

In recent years, research has increasingly focused on the economic value of freshwater ecosystems, which provide essential services such as water supply, climate regulation, and recreation, but are highly vulnerable to human-induced degradation. To examine this body of work, a meta-analysis was conducted on 116 studies regarding the economic value of ecosystem services provided by freshwater ecosystems, which collectively reported 368 valuations. The results indicate that 50.2% of the variation in existing value estimates can be explained by an econometric model that controls for (a) the geographical and socio-economic characteristics of the study site, (b) the valuation method and beneficiary type, and (c) the physical and ecological attributes of the specific biome and ecosystem service. The work illustrates the effect of different freshwater ecosystems on economic valuation estimates, also showing the impact of site and socio-economic characteristics of the study. Furthermore, the study

assesses the prospects for using the meta-analytic value function derived from the model, finding an average transfer error of 14.4%. This study effectively summarizes the existing literature on the economic value of freshwater ecosystems, allows for the establishment of stylized facts and provides the foundation for the development of tools to support environmental policy decisions.

Keywords: Natural capital · Water resource · Econometrics · Value function · Economic valuation methods · Ecosystem services · Freshwater ecosystem

JEL Classifications: Q51, Q57

1.1 Introduction

The way we observe and assign economic and social value to natural goods is one of the most relevant and controversial themes in modern society. A key piece of information for fully understanding the topic and developing appropriate public policy is the evaluation of the methodological framework underlying such assessments. Ecosystem assessment is likely to become a key area of work for National Statistical Institutes around the world (Grammatikopoulou et al., 2023), but the capacity to meet growing policy demands to date is limited.

In July 2022, the European Commission adopted the technical proposal (EU Commission, 2022) to amend Regulation 691/2011 on European environmental economic accounts to include the evaluation of ecosystems and biodiversity. In August 2022, the White House Office of Science and Technology Policy issued a report outlining the national strategy for the United States to create statistics for environmental economic decision-making (The White House, 2023). The report emphasizes the goal of incorporating nature into the country's economic accounts by advancing the development of natural capital accounts.

In March 2021 the United Nations Statistical Commission (UNSC) adopted the System of Environmental-Economic Accounting Ecosystem Accounting (SEEA EA) (Edens et al., 2022). The SEEA EA is an integrated and spatial statistical framework for organizing biophysical information on ecosystems, measuring the flows of ecosystem services (ES) generated, tracking changes in ecosystem extent and conditions, assessing ecosystem goods and services, and linking this information to measures of economic and human activity (United Nations, 2025).

Nevertheless, as Brander et al. (2022a) emphasize, there are several practical challenges concerning the monetary valuation of ES. The first challenge pertains to the consistency of measuring the exchange value of an ES with the National Accounting System. The exchange value represents the monetary measure of the underlying economic activity, which is manifested through transactions and market prices. However, many ES are not traded in markets due to their public good characteristics (non-excludability and non-rivalry) and lack of observable market prices.

To fill this knowledge gap, extensive research in the field of environmental economics has been undertaken, focusing on developing and applying methodologies to assess the values of non-market ES (de Groot et al., 2012; Freeman III et al., 2014). The second challenge concerns the spatial variability of determinants that shape the demand and supply of each ES (Bateman et al., 2002; Hein et al., 2006; Schaafsma, 2015). The supply is largely determined by ecological processes and characteristics that can be influenced by human activities. Factors influencing the demand, on the other hand, encompass socio-economic variables such as the number of beneficiaries, wealth, and the availability of substitutes and complements (Brander et al., 2022a).

The third challenge involves determining the appropriate geographical scale at which information on the value of ES is needed for accounting applications. The implementation of the SEEA EA can be carried out at different scales, e.g., local, regional, and national levels: in

all cases, it requires values of ES for multiple ecosystem units covering large geographic areas (Brander et al., 2022b). Finally, a fourth challenge concerns the high source of uncertainty in estimated ES values deriving from the use of different methodological approaches. Indeed, the development of methodologies and approaches to enhance the accuracy of these estimates is essential (United nations, 2021) and becomes a crucial area of investigation to allow the determination of the actual effects of public policies on ecosystems and biodiversity management.

These aspects are of great relevance concerning freshwater ecosystems. These ecosystems are characterized by unique biodiversity and contribute to essential services, such as water and food supply, climate regulation, and recreational opportunities (Janse et al., 2015). However, they are particularly vulnerable to degradation due to activities occurring within their respective hydrographic basins, which include rivers and lakes (Kummu et al., 2011). Given the increasing global anthropogenic pressure, the restoration and conservation of freshwater ecosystems emerge as urgent environmental priorities (Carvalho et al., 2019).

Since the end of the last century, many studies have employed a wide range of diverse procedures and different types of ES conceptualization to estimate economic value provided by various ecosystems (Arias-Arévalo et al., 2018; Bateman et al., 2011; Brander et al., 2006; Brouwer et al., 2013; Chen, 2020; Chu et al., 2020; Costanza et al., 1997, 2017; Grammatikopoulou and Vačkářová, 2021; de Groot et al., 2002; Navrud and Strand, 2018; Schild et al., 2018). Consequently, summarizing the burgeoning literature effectively and developing stylized facts has become challenging. Furthermore, due to the diverse conditions characterizing these studies, it is difficult to determine to what extent specific methodological choices can impact the estimates of the economic valuation of ES.

The purpose of this paper is to conduct a meta-analysis of the published studies reporting the monetary value of ES provided by freshwater ecosystems and to determine the effects of ecosystem characteristics, methods of economic valuation, and socio-economic factors on

valuation estimates. The objective is to generate a set of outcomes not strictly related to the peculiarities of one or more studies and to explore the potential applicability of the estimated meta-analytic value function in addressing the challenges described above.

The analysis encompasses not only individual freshwater biomes (i.e., lakes, rivers, and anthropogenic water structures) according to the International Union for Conservation of Nature ecosystem classification (Keith et al., 2022), but also transitional freshwater/terrestrial biomes (marshes, swamps, peatlands, seasonal floodplains) and freshwater/terrestrial/marine biomes (coastal wetlands, river deltas) that interact with each other and fall within the same realm of political, economic, and environmental management. These relationships are crucial for sustainable development. For instance, healthy freshwater biomes and their adjacent areas (e.g., floodplains) can serve as natural sponges and buffers against floods and storms (United Nations, 2025).

In the next section, we discuss the paper selection procedure and the assessment methodology, as well as the data collected from the selected studies and databases. Detailed results of the analysis are then presented, and an assessment of the potential application of the value function is provided. The final section covers concluding remarks and offers useful suggestions for future research.

1.2 Systematic Literature Review

A comprehensive search of published articles regarding the economic value of freshwater ecosystems was conducted in major academic journal publishers' databases (Scopus, Web of Science) using the query terms consisting of:*TITLE-ABS-KEY ("ecosystem service*" OR "ecological service*" OR "environmental service*") AND TITLE-ABS-KEY ("freshwater" OR "river*" OR "river delta*" OR "lake*" OR "marsh*" OR "swamp*" OR "floodplain marsh*" OR "peat*" OR "anthropogenic freshwater" OR "constructed wetland*" OR "canal*" OR "drain*" OR "rice padd*") AND TITLE-ABS-KEY ("market price*" OR*

"mitigation cost" OR "replacement cost" OR "avoided cost" OR "production function" OR "travel cost" OR "hedonic pric" OR "revealed preference" OR "stated preference" OR wtp OR wta OR wts OR "choice model*" OR "choice experiment" OR "group deliberation" OR "benefit transfer" OR "shadow price*" OR "simulated exchange").* The selection of keywords was based on the comprehensive collection of economic evaluation methods of ES provided by freshwater ecosystems (Bouma and Van Beukering, 2015; United Nations, 2025), as shown in Table 1, and the classification of the respective biomes (Keith et al., 2022).

Table 1: Main economic evaluation methods of ES provided by freshwater ecosystems

Approach	**Method**	**Technique**
Direct market valuation	Market price–based	market prices adjusted market prices
	Cost–based	replacement cost damage cost avoided mitigation cost
	Production function	
Indirect market valuation (revealed preferences)	Travel cost	
	Hedonic pricing	
Non–market valuation (stated preferences)	Contingent valuation	willingness to pay willingness to accept willingness to sell
	Choice modelling	
	Group deliberation	
	Shadow pricing	
Others	Benefit transfer (BT)	unit BT adjusted BT value function transfer meta–analysis
	Simulated exchange	

Source: SEEA EA, author's elaboration.

The search was then extended to the Ecosystem Services Valuation Database (ESVD), a database of primary studies (peer-reviewed, grey literature, and national reports) that includes the broadest collection and synthesis of information on the economic value of ecosystems

at a global scale (Brander et al., 2022a). The publication time frame included in the search criteria started from 2000 to March 2023 (time the search was conducted). In accordance with Deeksha and Shukla (2022), 2000 was set as the starting point because the number of articles focusing on the topic has increased significantly since that year. To obtain the list of studies to be considered for the review, a quality checklist (Page et al., 2021) and the following criteria have been considered: the study had to report an estimate of the economic value of a freshwater ecosystem or the services generated by this ecosystem type; if multiple articles from the same authors were based on identical datasets, only one of the studies (chronologically the first) was included in this analysis, the study had to report at least one estimate of the economic value of a freshwater ecosystem or the services generated by this type of ecosystem based on primary data.

In the process of study selection, a total of 994 articles were identified using the chosen keywords. Out of these articles, 430 were retrieved from the Web of Science database, 381 were found in the Scopus database, and 183 articles in the ESVD database. During the screening process, 149 articles were excluded as they were not relevant to the topic, 207 articles were excluded for not meeting the selection criteria, and 522 articles were excluded as duplicates, indicating the high level of consistency in the query results across different databases. Consequently, the final number of articles included in the meta-analysis amounted to 116, yielding a total of 368 assessments for the ES provided by freshwater ecosystems (each study can contain more than one assessment). The PRISMA diagram depicting the study selection process can be found in Supplementary Information (SI).

1.3 Meta-regression Model for the Monetary Value of ES and post-estimation Diagnostics

The meta-analysis is based on a multiple regression providing the expected value of the dependent variable (monetary value of ES) as a function of fixed values of the variables that

relate to the geographical and socio-economic characteristics of the study site, the valuation method and beneficiary type, and the physical and ecological attributes of the specific biome and ES. An exploratory analysis of the available literature data on the economic evaluation of ES provided by freshwater ecosystems did not allow for considering interactions among the various explanatory variables.

The meta-regression model was used to summarize and evaluate the results of previous research. To obtain marginal effects, given the potential interference of relevant characteristics, meta-regression analysis has been employed to assess the relative importance of all potentially relevant factors simultaneously. Our meta-regression model is specified in a log-log functional form (Eq. 1), where the dependent variable is the vector of the ES monetary values in International dollars per hectare per year in 2020 price level (adjusted using the purchasing power exchange rate). The explanatory variables are presented in Table 2 and are organized into three groups: site and socio-economic characteristics (Xss), study characteristics (Xst), and biome and ES characteristics (Xes). The estimating model is the following:

$$\ln y_{it} = \alpha + X_{ss,it}\beta_{ss} + X_{st,it}\beta_{st} + X_{es,it}\beta_{es} + \gamma_i + \varepsilon_{it} \tag{1}$$

where α represents the constant term, the vectors β_{ss}, β_{st}, and β_{es} refer to the coefficients associated with the time-varying and time-invariant explanatory variables in the Xss, Xst, and Xes groups, respectively, γ_i is the time invariant unobserved heterogeneity that differs across studies, ε_{it} is the idiosyncratic error term, and y_{it} corresponds to the individual monetary value estimated. A Breusch and Pagan Lagrangian multiplier test was performed to check the appropriateness of the panel structure. A Generalized Least Square model including random effects was then used as estimator to handle heterogeneity (Nelson and Kennedy, 2009). A Hausman's test was conducted to test for the consistency of the random effects model. For our dataset, with data on single monetary value with clustering on studies, we adapt panel data method that have clustered errors under the standard panel assumption of uncorrelated

errors across studies but error correlation over single observations. An important conceptual change from panel data cases was clustering on studies, not on single observations. The autocorrelation in panel structure was assessed by the Wooldridge test, that rejected the null hypothesis of serial correlation, confirming the efficiency of the estimator (Wooldridge, 2010).

Table 2: Summary statistics of explanatory variables

Explanatory variables (unit of measure)		Obs.	Mean	Std. dev.	Min	Max
Site and socio-economic characteristics (Xss)						
GDP per capita (PPP 2017) (nat. log)		368	23176.330	19560.390	1571.180	63027.680
Population density (people per km^2)		368	256.959	250.664	3.335	1286.172
Rural population (% total population)		368	39.999	22.417	7.764	82.573
No Protected	(1 = presence; 0 = otherwise)[a]	368	0.432	N.A.	0	1
Area (100 km^2) (nat. log)		368	9.329	30.261	0.000	168.260
Latitude		368	25.331	22.610	-45.408	54.500
Longitude		368	49.035	52.223	-110.568	146.130
National scale	(1 = presence; 0 = otherwise)[b]	368	0.024	N.A.	0	1
Regional scale	(1 = presence; 0 = otherwise)[b]	368	0.060	N.A.	0	1
Africa	(1 = presence; 0 = otherwise)[c]	368	0.188	N.A.	0	1
Asia	(1 = presence; 0 = otherwise)[c]	368	0.454	N.A.	0	1
North America	(1 = presence; 0 = otherwise)[c]	368	0.033	N.A.	0	1
Oceania	(1 = presence; 0 = otherwise)[c]	368	0.003	N.A.	0	1

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Explanatory variables (unit of measure)		Obs.	Mean	Std. dev.	Min	Max
South America	(1 = presence; 0 = otherwise)[c]	368	0.005	N.A.	0	1
Residents	(1 = presence; 0 = otherwise)[d]	368	0.272	N.A.	0	1
Study characteristics (Xst)						
Year		368	2010.217	5.333	2000	2022
Peer reviewed	(1 = presence; 0 = otherwise)[e]	368	0.611	N.A.	0	1
Choice experiment	(1 = presence; 0 = otherwise)[f]	368	0.068	N.A.	0	1
Contingent valuation	(1 = presence; 0 = otherwise)[f]	368	0.236	N.A.	0	1
Hedonic pricing	(1 = presence; 0 = otherwise)[f]	368	0.014	N.A.	0	1
Market price	(1 = presence; 0 = otherwise)[f]	368	0.383	N.A.	0	1
Production function	(1 = presence; 0 = otherwise)[f]	368	0.109	N.A.	0	1
Travel_cost	(1 = presence; 0 = otherwise)[f]	368	0.063	N.A.	0	1
Highly degraded or intensively managed	(1 = presence; 0 = otherwise)[g]	368	0.198	N.A.	0	1
Well-functioning or extensively managed	(1 = presence; 0 = otherwise)[g]	368	0.391	N.A.	0	1
Biome and ES characteristics (Xes)						

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Explanatory variables (unit of measure)		Obs.	Mean	Std. dev.	Min	Max
Coastal wetlands and River deltas	(1 = presence; 0 = otherwise)[h]	368	0.073	N.A.	0	1
Lakes	(1 = presence; 0 = otherwise)[h]	368	0.296	N.A.	0	1
Marshes and swamps	(1 = presence; 0 = otherwise)[h]	368	0.065	N.A.	0	1
Peatlands	(1 = presence; 0 = otherwise)[h]	368	0.008	N.A.	0	1
Rice paddies	(1 = presence; 0 = otherwise)[h]	368	0.079	N.A.	0	1
Rivers and streams	(1 = presence; 0 = otherwise)[h]	368	0.323	N.A.	0	1
Seasonal floodplain marshes	(1 = presence; 0 = otherwise)[h]	368	0.090	N.A.	0	1
Aesthetic information	(1 = presence; 0 = otherwise)[i]	368	0.084	N.A.	0	1
Climate regulation	(1 = presence; 0 = otherwise)[i]	368	0.054	N.A.	0	1
Existence, bequest	(1 = presence; 0 = otherwise)[i]	368	0.027	N.A.	0	1
Food	(1 = presence; 0 = otherwise)[i]	368	0.223	N.A.	0	1
Maintenance of biodiversity	(1 = presence; 0 = otherwise)[i]	368	0.063	N.A.	0	1
Moderation of extreme events	(1 = presence; 0 = otherwise)[i]	368	0.052	N.A.	0	1
Recreation and tourism	(1 = presence; 0 = otherwise)[i]	368	0.179	N.A.	0	1

Raw materials	(1 = presence; 0 = otherwise)[i]	368	0.082	N.A.	0	1

Notes. (a): reference is Protected areas, (b): reference is Local scale studies, (c): reference is Europe, (d): reference is Global beneficiaries' unit, (e): reference is grey literature, (f): reference is Cost-based methods (Damage cost avoided, Replacement cost, Mitigation cost), (g): reference is Intermediate ecological status, (h): reference is Anthropogenic structures, (i): reference is Water supply. N.A.: not applicable. For dichotomous variables, the proportion of the variable in the sample is reported in the mean column, and it is not possible to calculate the standard deviation.

Explanatory variables were selected based on literature reviews of similar meta-analysis studies and the underlying theory (Brander et al., 2006, 2022b; Brouwer et al., 1999; Reynaud and Lanzanova, 2017). Type of biomes and ES, valuation methods, and socio-economic characteristics such as membership in a protected area and geographic scale of assessment, have been introduced as dummy variables. Before defining the final meta-regression model, several alternative specifications of the model were examined. The dependent variable and the explanatory variables of GDP per capita (PPP 2017) and area were transformed into their natural logarithmic form based on the Shapiro-Wilk normality test (Shapiro and Wilk, 1965), which rejected the null hypothesis of normality for the estimated values. Multicollinearity was assessed by examining the average value of the Variance Inflation Factor (VIF). Independent variables with values of 1/VIF lower than the tolerance threshold of 0.1 should be excluded (O'brien, 2007). This is to show that the coefficient estimates of the regression model are stable, and the standard errors of the coefficients are not distorted. This model selection procedure is consistent with other meta-analysis studies (Barrio and Loureiro, 2010; Brander et al., 2006; Lindhjem, 2007; Loomis and White, 1996; Vedogbeton and Johnston, 2020; Brouwer et al., 2022).

The presence of publication bias was subsequently tested, which is a form of sample selection bias (Nelson and Kennedy, 2009). Standard methods for detecting potential publication bias in meta-regression models are founded on the premise that such biases often introduce a relationship between effect size estimates and their precision (Stanley, 2005). A dummy variable was then created for studies subjected to the peer-review process (61% of the sample) and entered as a model control variable (Brouwer et al., 2022).

1.4 Data Standardization

The way economic values are presented in primary studies shows considerable variation. Some studies present economic values per hectare, while others use biophysical units or visit

measures. This variability depends on the specific ES under examination. To allow comparison of different years and different currencies, the economic values have been standardized in international monetary units, specifically the US dollar per hectare per year in 2020 price level adjusted using the purchasing power exchange rate (Int\$2020 ha^{-1} $year^{-1}$) (Brander et al., 2024). For example, for the travel cost method, standardization of the value reported in the primary study was done by aggregating the value for total beneficiaries (derived by secondary data e.g., average annual site visits) divided by the size of the ES delivery area.

Furthermore, studies show high variability in the classification of biomes, ES, and evaluation methods, necessitating an effort to standardize the data. Each freshwater biome has been categorized according to the IUCN ecosystems classification (Keith et al., 2022) and valuation methods were classified in line with the SEEA EA framework (United Nations, 2025).

The estimated economic values of ES encompass all forms of value concepts (i.e., well-being, exchange, and other) and both marginal and average values (Bateman et al., 2013; Woodward and Wui, 2001). Therefore, it was necessary to take into account these conceptual dimensions in the selection of value data to be considered in the econometric model. Thus, the studies were evaluated based on the ecological status of the target area (highly degraded or intensively managed, intermediate, well-functioning or extensively managed), the type of beneficiaries of the specific ES (residents or global), the scale of application (local, regional, or national), the socio-economic characteristics (Gross Domestic Product (GDP) per capita Purchasing Power Parity (PPP) constant 2017 international \$), population density, share of rural population, belonging to a protected area) and the geographics ones (latitude, longitude, study area, Continent).

1.5 Potential meta-analytic Value Transfer Application

The coefficient estimates of the meta-regression model for the economic value of ES can be used to forecast the values of certain ES provided by freshwater biomes. The values

of the explanatory variables in the new application site were selected, multiplied by their corresponding coefficients, and then aggregated (Johnston et al., 2018). This sum corresponds to the natural logarithm of the predicted value of ES for the biome.

To verify the accuracy of the values obtained using the meta-analytical value function, transfer errors were calculated:

$$TE = \frac{Value_{transf} - Value_{obs}}{Value_{obs}} \tag{2}$$

where TE indicates the transfer error, $Value_{transf}$ and $Value_{obs}$ are the estimated and the observed economic value of the ES, respectively (Kirchhoff et al., 1997). A small transfer error implies accuracy in the transferred values. Transfer errors are classified into four main categories (Boyle and Parmeter, 2017): $|TE| \leq 0.2$ suggests a good fit; $0.2 < |TE| \leq 0.5$ indicates adequate fit; $0.5 < |TE| \leq 1$ corresponds to poor fit; $|TE| > 1$ implies very poor fit, and forecasts should be treated with caution. Value transfer may incur transfer errors due to comparability issues between different sites or incorrect specification of variables (Brouwer, 2000). For the analysis of transfer error, the jackknife delete-one method (Efron, 1982; Efron and Tibshirani, 1994) was used to estimate $n - 1$ value transfer functions by applying the estimated parameters generated with $n - 1$ observations to the omitted observation. However, it is important to emphasize that the level of transfer errors and the degree of accuracy depend on the new site of application context (Johnston et al., 2021). Further, to eliminate the impact of very high and low values, the sample was trimmed by 10% of the extreme values (OECD, 2012).

1.6 Preliminary Descriptive Results

Of the selected studies, 46.6% focus on Asia, 24% on Europe, and 22% on Africa. The least represented continents are America (6% of the studies) and Oceania (0.9%). Considering the

116 selected primary valuations, it was observed an average economic value for freshwater ES of 21,473 Int$2020 ha^{-1} $year^{-1}$. The median value is 442 Int$2020 ha^{-1} $year^{-1}$, indicating a right-skewed distribution. The average value of ES provided by Anthropogenic freshwater structures is 27,075 Int$2020 ha^{-1} $year^{-1}$, higher than the corresponding value for Rivers and streams biomes (5,508 Int$2020 ha^{-1} $year^{-1}$) and Coastal wetland and River deltas biomes (1,151 Int$2020 ha^{-1} $year^{-1}$) (Table 3). On average, the values found for ES provided by Freshwater lakes (45,643 Int$2020 ha^{-1} $year^{-1}$) are much higher than those reported by Reynaud and Lanzanova (2017) (315 Int$2010 ha^{-1} $year^{-1}$). This difference can be attributed to the distinct price levels used to standardize the estimate values and to the evolution that studies on the value of ES have undergone in the last decades: Reynaud and Lanzanova (2017) consider studies performed in 1972–2012, in this study on the period 2000–2023.

The meta-regression model allows assessment of how a specific type of ES associated with the biome contributes to the economic valuation. Freshwater lakes, for example, receive the highest evaluation in studies analyzing the ES of Opportunities for Recreation and Tourism (obs. = 20), with an average value of 201,723 Int$2020 ha^{-1} $year^{-1}$. On the other hand, studies that evaluated 'Water supply service' for the same biome (obs. = 26) gave an average valuation of 3,836 Int$2020 ha^{-1} $year^{-1}$ (Table 3).

Regarding the methodological applications, the data showed that the choice of the evaluation method is based on the type of ES to be assessed, as also highlighted in Grammatikopoulou and Vačkářová (2021). For instance, the Market Prices method, which has the highest number of observations (141), is preferred for provisioning services related to 'Food and Water supply'. On the other hand, out of the 87 observations in which Contingent Valuation methods were used, 13.8% was for the evaluation of the 'Maintenance of biodiversity service', 25.3% for 'Water supply service', and 26.4% for 'Recreation and tourism service', highlighting potential for application to different types of services (Table 4).

Table 5 presents the average ES values per evaluation method. 'Recreation and Tourism'

service received a higher average valuation (66,538 Int$2020 ha^{-1} year^{-1}), while 'Food' has the highest valuation (10,114 Int$2020 ha^{-1} year^{-1}) compared to others provisioning services of 'Water supply' (6,529 Int$2020 ha^{-1} year^{-1}) and 'Raw materials' (5,793 Int$2020 ha^{-1} year^{-1}).

The only valuation method applied for all types of ES is Market prices, which uses the prices of ES traded in the markets as a proxy for their monetary value (Arias-Arévalo et al., 2018). The Contingent Valuation method, which relies on direct inquiries to beneficiaries estimating willingness to pay, accept, and sell (WTP, WTA, and WTS), is also widely used in the studies included in the sample (Chang and Yoshino, 2017; Endalew et al., 2020). High average values emerged with the Replacement Cost method (10,896 Int$2020 ha^{-1} year^{-1}) and the Production Function method (10,936 Int$2020 ha^{-1} year^{-1}). The former estimates the value of an ES as the costs associated with its replacement, while the latter assumes that the value of an ES can be estimated from its contribution to the enhancement of income or productivity (Pascual et al., 2010). Among the methods of indirect valuation (revealed preference), where the value is observable from the behavior of ES consumers, the Travel Cost method is prevalent for cultural ES of Recreation and Tourism, while the Hedonic pricing method is mainly used to value the ES of Aesthetic Information. The former measures the costs associated with the enjoyment of a recreational service, while the latter assumes that the value of an ES is partially contained in the price of a good that benefits from the presence of such a service, typically with an aesthetic value (Sander and Haight, 2012).

Table 3: Mean monetary value for each biome related to the specific ES (Int$2020 $ha^{-1}year^{-1}$)

Biome	Ecosystem Service																	
	Aesthetic information		**Climate regulation**		**Existence bequest**		**Food**		**Biodiversity maintenance**		**Extreme Events**		**Recreation tourism**		**Raw materials**		**Water supply**	
	Mean *(st. dev.)*	Obs.	Mean *(st. dev.)*	Obs.	Mean *(st. dev.)*	Obs.	Mean *(st. dev.)*	Obs.	Mean *(st. dev.)*	Obs.	Mean *(st. dev.)*	Obs.	Mean *(st. dev.)*	Obs.	Mean *(st. dev.)*	Obs.	Mean *(st. dev.)*	Obs.
Lakes	11,348 *(32,695)*	13	266 *(356)*	4	16,359 *(28,292)*	3	21,381 *(86,122)*	23	7,248 *(13,818)*	8	19,602 *(30,264)*	3	201,723 *(889,600)*	20	3,847 *(11,044)*	9	3,836 *(7,779)*	8
Rice paddies			8,522 *(9,204)*	5	176,105 *(305,021)*	3	31,164 *(37,072)*	10	681 *(962)*	2	1,872 *(2,837)*	4	1,235 *(//)*	1			77 *(152)*	4
Anthropogenic freshwater systems	63,203 *(86,421)*	2			2,843 *(3,680)*	2	159 *(//)*	1			62,782 *(91,164)*	3	7,551 *(16,811)*	8			33,598 *(81,266)*	8
Seasonal floodplain marshes	565 *(//)*	1					26,405 *(55,476)*	12	277 *(221)*	4			440 *(//)*	1	11,992 *(16,096)*	8	549 *(1,088)*	7
Marshes and swamps	9,024 *(7,808)*	3	7,443 *(12,536)*	4			11,342 *(10,886)*	4	42,630 *(44,970)*	2	2,112 *(1,609)*	2	12,839 *(2,931)*	2	42,218 *(//)*	1	1,610 *(2,490)*	6
Rivers and streams	767 *(1,248)*	12	13,292 *(25,914)*	7	25,942 *(32,649)*	2	2,255 *(5,229)*	18	692 *(870)*	6	420 *(678)*	7	8,414 *(11,835)*	32	302 *(278)*	3	5,734 *(17,006)*	32
Coastal wetlands and river deltas					2,941 *(5,029)*	12	3,097 *(//)*	1			52 *(70)*	2	14 *(34)*	8	548 *(823)*	4		
Peatlands					15 *(17)*	2												

The italic values indicate standard deviations

Table 4: Economic evaluation methods used, and relative weight of the specific ES valuated

Valuation method	Ecosystem Service									Obs
	Aesthetic information	**Climate regulation**	**Existence, bequest values**	**Food**	**Maintenance of biodiversity**	**Moderation of extreme events**	**Recreation and tourism**	**Raw materials**	**Water supply**	
Market prices	0.7%	2.8%	0.7%	36.1%	1.4%	4.2%	14.9%	14.9%	24.1%	141
Contingent Valuation	18.4%	1.1%	3.4%	6.9%	13.8%	4.6%	26.4%	//	25.3%	87
Production function	//	2.5%	//	47.5%	5.0%	//	5.0%	22.5%	17.5%	40
Replacement cost	//	27.8%	5.6%	2.8%	13.9%	19.4%	2.8%	//	27.8%	36
Choice Experiment	16.0%	4.0%	12.0%	20.0%	8.0%	8.0%	8.0%	//	24.0%	25
Travel cost	26.1%	//	//	//	//	//	73.9%	//	//	23
Damage cost avoided	//	37.5%	//	//	//	//	//	//	62.5%	8
Hedonic pricing	80.0%	//	20.0%	//	//	//	//	//	//	5
Opportunity cost	//	//	//	//	//	//	//	//	100.0%	3

Table 5: Mean ES monetary values according to applied valuation method (Int$2020 ha^{-1} $year^{-1}$)

Ecosystem service	Valuation method																		Total
	Choice Experiment		**Contingent Valuation**		**Damage cost avoided**		**Hedonic pricing**		**Market prices**		**Opportunity cost**		**Production function**		**Replacement cost**		**Travel cost**		
	Mean *(st. dev.)*	Obs.	Mean *(st. dev.)*	Obs.	Mean *(st. dev.)*	Obs.	Mean *(st. dev.)*	Obs.	Mean *(st. dev.)*	Obs.	Mean *(st. dev.)*	Obs.	Mean *(st. dev.)*	Obs.	Mean *(st. dev.)*	Obs.	Mean *(st. dev.)*	Obs.	obs.
Recreation and tourism	653 *(765)*	2	11,350 *(12,852)*	23	//	//	1,924 *(2,222)*	21	//	//	4,244 *(4,115)*	2	49,028 *(//)*	1	237,134 *(964,832)*	17	//	//	66
Existence, bequest values	5 *(6)*	3	176,198 *(304,941)*	3	//	//	5,445 *(//)*	1	//	//	//	//	//	//	//	//	//	//	10
Food	//	//	13,138 *(21,697)*	6	//	//	//	//	8,558 *(20,062)*	51	//	//	16,511 *(45,372)*	19	413 *(//)*	1	//	//	82
Moderation of extreme events	1 *(1)*	2	4,508 *(9,004)*	4	//	//	//	//	39,045 *(66,321)*	6	//	//	//	//	1,358 *(1,165)*	7	//	//	19
Aesthetic information	1,015 *(1,533)*	4	17,437 *(40,823)*	16	//	//	488 *(//)*	4	80 *(//)*	1	//	//	//	//	//	//	4,282 *(8,544)*	6	31
Climate regulation	40 *(1)*	1	2 *(//)*	1	4 *(//)*	3	//	//	778 *(647)*	4	//	//	141 *(//)*	1	16,318 *(21,069)*	10	//	//	20
Maintenance of biodiversity	1,050 *(585)*	2	11,202 *(22,958)*	12	//	//	//	//	477 *(140)*	2	//	//	384 *(539)*	2	2,943 *(4,511)*	5	//	//	23
Water supply	12 *(18)*	6	6,004 *(19,272)*	22	1,012 *(666)*	5	//	//	9,621 *(40,167)*	34	7,530 *(12,584)*	3	3,394 *(2,777)*	7	5,737 *(12,023)*	10	//	//	83
Raw materials	//	//	//	//	//	//	//	//	3,962 *(11,380)*	21	//	//	10,067 *(15,907)*	9	//	//	//	//	30

The italic values indicate standard deviations

1.7 Meta-regression Model post-estimation Diagnostics and Results

Generalized least squares including random effects was performed. The Breusch-Pagan Lagrangian multiplier test indicated that the variance components in the random effects model were significantly different from zero. The Hausman test was then conducted to evaluate the consistency of the random effects estimator with respect to the coefficients of the fixed effects model (Prob $>$ χ^2 = 0.664). The test allowed to compare the estimable coefficients of time-varying regressors and to estimate the coefficients of time-invariant regressors. The Wooldridge test for autocorrelation led to the rejection of the null hypothesis of the presence of serial correlation (Prob $>$ F = 0.238). Multicollinearity was assessed by examining the Variance Inflation Factor (VIF), which had an average value of 4.27.

The estimated meta-regression model (Table 6) explains 50.2% of the variance in the dependent variable, as indicated by the overall R-square value, and the 52.4% of the between studies variance.

Table 6: Meta-regression model results

Explanatory Variables (unit of measurement)		**Coefficient**	**Std. err.**	$P > \|z\|$
Site and socio-economic characteristics (Xs)				
Ln_GDP per capita (PPP 2017)		-2.110	0.844	0.012**
Population density (people per km^2)		-0.002	0.001	0.170
Rural population (% total population)		-0.101	0.030	0.001***
No Protected	(a)	1.031	0.615	0.093*
Ln_Area (100 km^2)		-0.296	0.093	0.001***
Latitude		0.060	0.024	0.013**
Longitude		0.012	0.016	0.438

Continue

Table 6: Meta-regression model results

Explanatory Variables (unit of measurement)		**Coefficient**	**Std. err.**	$P > \|z\|$
National scale	(b)	4.907	1.914	0.009***
Regional scale	(b)	1.418	1.292	0.273
Africa	(c)	-0.436	1.933	0.822
Asia	(c)	0.971	1.628	0.551
North America	(c)	-0.374	2.430	0.878
South America	(c)	1.927	3.223	0.550
Oceania	(c)	6.070	4.043	0.813
Study characteristics (Xs)				
Residents	(d)	-0.121	0.741	0.870
Year		-0.089	0.060	0.135
Peer Reviewed		-0.767	0.655	0.241
Choice experiment	(e)	-3.863	1.197	0.001***
Contingent valuation	(e)	-0.728	0.559	0.192
Hedonic price	(e)	-0.898	0.984	0.361
Market price	(e)	0.386	0.415	0.352
Production function	(e)	0.578	0.685	0.399
Travel cost	(e)	0.232	0.696	0.739
Biome and ES characteristics (Xes)				
Highly degraded or intensively managed	(f)	-0.513	0.793	0.518
Well-functioning or extensively managed	(f)	0.239	0.599	0.690
Coastal wetlands and River deltas	(g)	-2.489	1.186	0.036**

Continue

Table 6: Meta-regression model results

Explanatory Variables (unit of measurement)		**Coefficient**	**Std. err.**	$P > \|z\|$
Lakes	(g)	-1.475	0.601	0.014**
Marshes and swamps	(g)	0.038	1.265	0.976
Peatlands	(g)	-6.723	2.996	0.025**
Rice paddies	(g)	-1.548	1.002	0.122
Rivers and streams	(g)	-2.235	0.674	0.001***
Seasonal floodplain marshes	(g)	-0.411	0.901	0.648
Aesthetic information	(h)	0.181	0.563	0.747
Climate regulation	(h)	-0.816	0.536	0.128
Existence, bequest	(h)	0.877	0.718	0.222
Food	(h)	-0.351	0.357	0.325
Maintenance of biodiversity	(h)	-0.239	0.561	0.699
Moderation of extreme events	(h)	0.274	0.548	0.617
Recreation and tourism	(h)	0.059	0.433	0.892
Raw material	(h)	-1.446	0.504	0.004***
Constant		209.743	122.139	0.086*
N			368	
R-squared overall			0.502	
R-squared within			0.088	
R-squared between			0.524	
ρ			0.614	

Continue

Table 6: Meta-regression model results

Explanatory Variables (unit of measurement)	**Coefficient**	**Std. err.**	$P > \|z\|$

Note: Dependent variable is ES monetary value (Int\$2020 ha^{-1} year^{-1})

Note: ***, **, and * are significant at the 1, 5, and 10% levels, respectively

Note: Standard errors adjusted for 116 clusters (number of studies)

[a] reference is Protected areas

[b] reference is Local scale studies

[c] reference is Europe

[d] reference is Global beneficiaries' unit

[e] reference is Cost-based methods (Damage cost avoided, Replacement cost, Mitigation cost)

[f] reference is Intermediate ecological status

[g] reference is Anthropogenic structures

[h] reference is Water supply

In the group of variables of site and socio-economic characteristics (Xss), GDP per capita shows a statistically significant effect, in line with Brander et al. (2006) and in contrast to Reynaud and Lanzanova (2017). As indicated in previous studies for other types of ecosystems (Chiabai et al., 2011; Ojea et al., 2010), the size of the area has a negative and statistically significant coefficient indicating diminishing marginal utility, it is to be expected that larger areas will have lower unit values. Studies conducted on a National scale led to higher ES values with respect to local scale studies, with a significant marginal effect of 4.907 (yi). There is also a negative and significant relationship between the percentage of rural population and ecosystem value. This relationship, however, is inelastic, and on average, urban biomes have a significantly higher value than rural ones.

Among the study's characteristics (Xst), only one explanatory variable was able to explain the variation in monetary value of ES at a statistically significant level. Focusing on evaluation methodologies, the value estimates obtained with revealed and stated preference approaches

were lower compared to the reference method based on costs, with a consistently significant statistical level for the Choice Experiment method. Similar findings were reported in Brander et al. (2006) regarding the direction of the estimated effect. No publication bias was detected since the peer reviewed studies does not affect the values in comparison to the studies from grey literature.

Among the biomes, Coastal Wetlands and River Deltas, Lakes, Peatlands and Rivers and Streams have been associated with lower per hectare values with respect to anthropogenic structures, showing statistical significance. Noteworthy is the evaluation of Rivers and streams in comparison to Anthropogenic freshwater structures, which is lower with a statistical significance level of 1%. This difference becomes even more pronounced when assessing the transitional biomes of Peatlands. Regarding the ES variables (Xes), we observed that none of the categories showed statistical significance compared to the reference ES (Water Supply), except for the Raw Material service, which received lower evaluation. The ES of Maintenance of biodiversity and Climate regulation showed smaller negative coefficients, although not statistically significant. Similar results are reported in Brander et al. (2006).

1.8 Potential Application of Meta-analytic Value Function

Results of the meta-analysis can be used to estimate monetary value of ES provided by freshwater ecosystems at different scale. The mean absolute error (Eq. 2) on our trimmed sample of 330 observations is 0.144. However, due to the complexity of factors in the studies analyzed, it is important to assess the robustness of these results in relation to the inclusion/exclusion of some studies. This is important from the "benefit transfer" point of view mentioned earlier. How accurate is our model in generating out-of-sample predictions? To answer these questions, a 'leave-one-out' exercise was conducted, which consists of deleting a observation, re-estimating the model, and using the model's estimates to predict the monetary value for the deleted observation. It was then used an $n-1$ data splitting technique to

estimate 329 value transfer functions by applying the estimated parameters generated with $n-1$ observations to the omitted observation.

Figure 1 presents the observed and predicted values of freshwater ecosystems in ascending order of observed values.

This shows that for a certain number of observations, there is a significant difference between the observed and predicted values. It also indicates that our value transfer function tends to overestimate very low values and slightly underestimate high values, consistent with the findings of Brander et al. (2006). The overall average transfer error is 0.144 which can be considered a good fit (Boyle and Parmeter, 2017). The average transfer error for the quartiles of the ordered by value data series, in ascending order, is 0.848, 0.134, -0.051, and -0.255, respectively. Compared to other value transfer applications, our results appear as good alternative for value transfer (Brouwer, 2000).

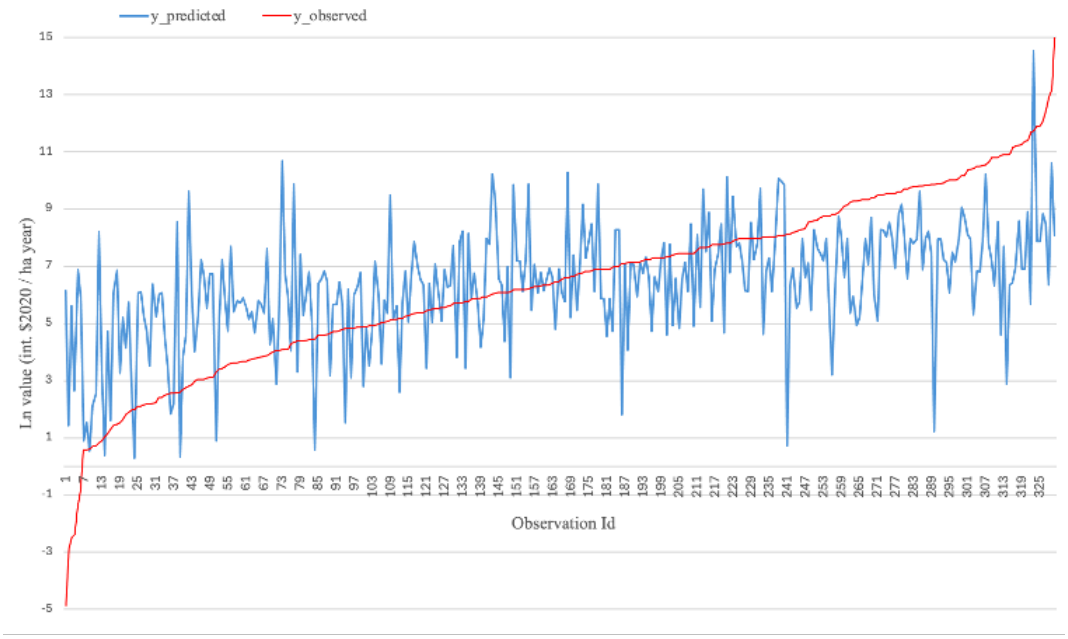


Figure 1: Observed and predicted freshwater ecosystem value, ranked in ascending order for observed values.

1.9 Conclusion

Although several studies have been conducted to investigate the economic value of ES associated with freshwater ecosystems, assimilating the results from the existing literature is difficult. This study performs a meta-analysis of 116 studies reporting a total of 368 valuations worldwide. The literature on freshwater ecosystem economic valuation has proven to be extremely variable in terms of estimated values, types of ecosystems considered, and valuation methods used. The estimated values produced by different valuation methodologies may not be inherently comparable and require explicit modeling in the meta-regression. A key outcome from our meta-regression analysis underscores the lack of significance of the coefficients associated with the methodological approach utilized. It emerges that the only significant approach is related to the non-market valuation techniques of Choice Experiments, which generate a lower value estimate compared to cost-based methods and direct market valuations. This result reveals the nature of cost-based techniques, such as Replacement cost, which is not directly related to value but is a proxy for it in the absence of direct valuations. It should also be noted that monetary values are a mix of market and non-market values, and an important conclusion is that most economic value is outside the market and can only be captured by non-market valuation techniques. These non-market values, although present, are still largely undervalued (Brander et al., 2024).

The robustness of our meta-regression for value transfer was also examined. The resulting average transfer error is comparable to other value transfer exercises reported in the literature. This level of transfer error may be deemed acceptable when considering transferred values as inputs in freshwater ecosystem conservation decisions. It should be noted, however, that although our data cover a wide variety of countries, some regions (America and Oceania) are underrepresented. This makes it difficult to transfer benefits globally. An important area for potential enhancement in the application of the proposed meta-analytical value function lies in addressing ecosystem quality. As currently formulated, the method primarily focuses

on the quantity or extent of ecosystems and does not adequately account for changes in quality. Incorporating ecosystem quality into the value transfer process would necessitate the definition and inclusion of multiple quality-related variables in both the assessment data underlying the meta-analysis and the data pertaining to the ecosystem networks to which values are transferred.

Another limitation of the present study is associated with the difficulty in distinguishing between ES to account for the diverse characteristics of demand and supply. Concerning demand, the effects on population and income are treated uniformly across all services. Regarding supply, it was implicitly assumed that the provision of all ES is proportionate to the geographical size of the ecosystem sites. An approach involving service-specific value transfers should take these differences into account, which could be achieved through service-specific meta-analytical value functions, as previously suggested by Brander et al. (2022b).

Further research efforts are needed to deepen the assessments of the main factors determining the value of ecosystems. Further avenues for investigation include the integration of primary valuation studies with external spatial data (e.g., GIS data) to model the effects of substitutes (varying in space), and geopolitical boundaries (Badura et al., 2020; Schaafsma and Brouwer, 2020). The increasing availability of georeferenced information and big data analytics provides an ideal context for developing spatially explicit value transfer approaches.

This analysis leads to conclude that previous research has indeed identified the values associated with freshwater ecosystems, given a particular biome. However, a more complex issue will lie in informing policymakers about which valuation estimates are most suitable for use in cost-benefit analysis and the ensuing management policies for these ecosystems.

2 Understanding Winegrowers' Adoption of Sustainable Practices in Eco-Schemes:Risk Attitudes and Perceptual Conditioning of the Probability of Impact on Net Returns

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Abstract

As part of the CAP reform for the 2023–2027 period, the environmental ambition that Member States are required to achieve has been heightened. The policy instrument expected to play a key role in this framework is the introduction of new eco-schemes under the first pillar. However, to achieve substantial benefits, they should prioritize measures that have been proven effective in meeting environmental objectives and be both financially attractive and administratively simple to elicit the expected behavioral response from farmers. This study explores winegrowers' willingness to adopt on-field sustainable practices under the framework of eco-schemes. Voluntary participation in such programs depends on multiple factors, including conservation intensity, incentive structures, monitoring requirements, business benefits, and adoption risks. Risk perception and preferences are key determinants of farmers' decision-making, particularly in high value-added sectors like the wine industry. Using a discrete choice experiment, we estimate winegrowers' willingness to accept monetary in-

centives for adopting specific practices, such as spontaneous and pollinator-friendly inter-row cover cropping, minimal soil tillage, and pesticide- or herbicide-free practices. These aspects were investigated by incorporating a nonlinear expected utility component into a random-parameter logit regression. This component accounted for the influence of the stochastic nature of net returns on the subjective valuation of winegrowers through a probability weighting function. This study contribution to literature is multifaceted. First, we estimate the monetary incentives required to encourage adoption, sustain continuity, and ensure additionality. We find evidence of a willingness to pay among producers who have already implemented certain practices, such as herbicide-free management, suggesting that experience shifts cost-benefit perceptions over time. Second, we assess winegrowers' attitudes toward net return fluctuations, considering how risk perception and preferences influences decisions to adopt agronomic practices beyond short-term productivity goals. Our results also reveal winegrowers prefer market-based incentive program and private managed monitoring system. By improving understanding of decision-making in sustainable viticulture, this research provides insights for designing targeted policies that align with sector-specific preferences and constraints.

Keywords: Risk preferences; Sustainable practices adoption; Eco-schemes; Additionality; Viticulture; Chice experiments; Nonlinear utility.

JEL Classifications: C83, C25, Q17.

2.1 Introduction

The global food system is the primary driver for the loss of biodiversity and the decline of related land and freshwater ecosystem services (Benton et al., 2021). Within the European

Union (EU), approximately 36% of the land consists of privately owned cultivated soils (EUROSTAT, 2023). With an allocated budget of 387 billion euros for the 2021–2027 period. With the total utilized agricultural area (UAA) estimated in 2020 being 157.4 million hectares, this means about €2,400/ha, and €400/ha/year. With this level of planned expenditure the EU's Common Agricultural Policy (CAP) is expected to have a significant impact on the management of natural capital (Pe'Er et al., 2022).

As part of the CAP reform for the 2023–2027 period, the environmental goals that Member States are expected to achieve has been broadened. The policy instrument expected to play a key role in this framework is the introduction of new eco-schemes under the first pillar (Runge et al., 2022). Conceptually similar to the agri-environmental and climate measures (AECM) of the second pillar, eco-schemes operate on a voluntary basis to support the adoption of sustainable agricultural practices. They can act as an intermediate instrument between conditionality (minimum standards) and AECM, designed for areas with complex ecological requirements (Pe'Er et al., 2022).

Farmers' access to these incentives initially depends on the "areas of action" that their respective Member States have prioritized as specific environmental objectives. Among the fifteen Member States analyzed by Runge et al. (2022), fourteen have identified biodiversity conservation as an area of action, with eleven explicitly designating it as a priority through targeted measures. By 2025, eco-schemes are expected to double the CAP budget allocated to biodiversity conservation programs compared to current AECM investments. However, to achieve substantial benefits, they should prioritize measures that have been proven to be effective in meeting environmental objectives. To elicit the expected behavioral response from farmers (Hasler et al., 2022), they also need to be both financially attractive and administratively simple.

What makes farmers adopt sustainability-oriented practices is a multifaceted and varied set of reasons. They include how they perceive context-specific benefits, the skills required

for the delivery of expected outcomes, and adequate knowledge of costs and benefits (Bennett et al., 2018; Pannell and Claassen, 2020). While the motivations for voluntary participation in incentive-based programs differ, economic considerations and business risk play a central role (Piñeiro et al., 2020). Risk perception and preferences are key determinants of farmers' decision-making (Just and Just, 2016). These are particularly relevant in high value-added sectors. The wine industry, where a de-commodification process has already occurred (Amatucci et al., 2024), is one of such sectors.

This study explores winegrowers' willingness to adopt on-field sustainable practices under the framework of eco-schemes. Voluntary participation in such programs depends on multiple factors, including conservation intensity, incentive structures, monitoring requirements, business benefits, and adoption risks. Using a discrete choice experiment, we estimate winegrowers' willingness to accept (WTA) monetary incentives for adopting specific practices, such as spontaneous and pollinator-friendly inter-row cover cropping, minimal soil tillage, and pesticide- or herbicide-free practices. While discrete choice experiments are widely used to inform policymakers about the design of incentive-based programs for sustainable agriculture (Gramig and Widmar, 2018; Latacz-Lohmann and Breustedt, 2019; Canales et al., 2024), key program attributes, such as risks associated with adoption, benefits from market dynamics or corporate assets, and the role of public versus private monitoring systems, remain underxplored.

This study contributes to the literature in several ways. First, we estimate the monetary incentives required to encourage adoption, sustain continuity, and ensure additionality. We find evidence of a willingness to pay (WTP) among producers who have already implemented certain practices, such as herbicide-free management, suggesting that experience shifts cost-benefit perceptions over time. Second, we assess winegrowers' attitudes toward the fluctuations of net returns by considering how risk perception and preferences influence decisions to adopt agronomic practices beyond short-term productivity goals. Our results also

reveal winegrowers prefer market-based incentive program and a monitoring system operated by independent third parties. By improving our understanding of decision-making in sustainable viticulture, this research provides insights for designing targeted policies that align with sector-specific preferences and constraints.

2.2 Background and Theory

2.2.1 Adoption of sustainable practices for the provision of ecosystem services and incentive-based programs

Sustainable practices aimed at delivering ecosystem services related to tree crops align with six of the eight action areas outlined in the EU's CAP: climate mitigation, climate adaptation, water protection, soil protection, biodiversity conservation, and the sustainable and reduced use of pesticides. The practices analyzed in this study are a representation of eco-schemes 2 and 5 proposed in Italy's CAP Strategic Plan (2022) and also integrated into the regulatory frameworks of France (France's CAP Strategic Plan, 2022) and Spain (Spain's CAP Strategic Plan, 2022). These frameworks collectively cover 34.1% of the world's vine area (International Organisation of Vine and Wine, 2024). Practices are defined as follows:

1. *Inter-row spontaneous cover crops*: ensure the presence of spontaneous or sown herbaceous vegetative cover in the inter-row area between September 15 and May 15 of the following year. Vegetative cover must be maintained on at least 70% of the surface area under commitment.

2. *Inter-row pollinator-friendly cover crops*: maintain, within the year of commitment, a vegetative cover specifically dedicated to pollinators, using plants of interest (nectariferous and polleniferous species) sown in the inter-row area. This requirement applies to a contiguous area of at least 0.25 hectares. Maintenance of the cover may involve

sowing the specified plants. Vegetative cover must be ensured on at least 70% of the surface area under commitment.

3. *Minimum soil tillage*: refrain from soil tillage in the inter-row area throughout the year. Any sowing method is permitted, provided it does not involve soil tillage.

4. *No herbicides*: Avoid the use of chemical herbicides. Manage herbaceous vegetative cover exclusively through mechanical operations, such as mowing, shredding, or mulching of the vegetation, throughout the year.

5. *No pesticides during flowering*: do not apply phytosanitary products during the flowering period of both the tree crop and/or the pollinators-specific crops. This prohibition applies from March 1 to September 30 over the entire surface area under commitment. During the remainder of the year, adopt integrated pest management practices.

The selected practices represent an improvement in the management of natural capital and entail increased efforts by farms, both in terms of economic investment and specialized knowledge, as well as an assumption of production risk, whether implemented individually or in combination. Furthermore, these practices provide environmental benefits not only to the vineyard itself (a company asset) but also beyond the boundaries of the farm. These benefits include soil carbon sequestration, reduced soil erosion, runoff mitigation, and biodiversity conservation (Giffard et al., 2022; Volanti et al., 2022).

Given the benefits these practices offer in terms of biodiversity conservation and the provision of ecosystem services, current adoption rates may fall short of socially optimal levels. Some sustainable practices, such as spontaneous inter-row cover crops and no-herbicides, which enhance carbon sequestration, reduce soil erosion and preserve soil biodiversity, are already adopted in some productive areas. However, more specific versions of these practices, such as those tailored for pollinators or intensified approaches that exclude pesticide use

during flowering, are adopted much less frequently (Bandinelli et al., 2020; Carroquino et al., 2020).

The decision of winegrowers to adopt a specific practice, whether within or outside an incentive program, is not independent of the production context, encompassing both social and pedo-climatic factors. Such practices may represent agronomic choices aimed at improving production or strategic decisions associated with branding (Garini et al., 2017). Moreover, certain practices are complementary, while others are mutually exclusive (e.g., spontaneous cover crops versus pollinator-friendly cover crops). Winegrowers can benefit from bundling practices, leveraging decreasing marginal costs (Pomarici et al., 2015). The synergies generated by adopting agricultural practices can lead to greater environmental benefits on a broader scale than that of individual farms. Sigwalt et al. (2012) identified aggregation effects and complementarities among practices and point out how this can play in favor of intensifying biodiversity conservation and preserving natural capital (Canales et al., 2020).

2.2.2 Market-based incentives and private monitoring

We evaluate winegrowers' preferences for incentive payment mechanisms implemented through either state-led or market-based programs. The delivery of ecosystem services resulting from the adoption of sustainable practices holds significant value for society (United Nations, 2025). Establishing a market for these services has the potential to promote dynamic economic efficiency, ensuring the continuous provision of services at reduced costs, while also serving as a crucial driver for the adoption of such practices (Ferraro et al., 2005; Ribaudo et al., 2010). To date, programs aimed at encouraging the adoption of voluntary sustainable practices have relied heavily on subsidies. These subsidies are provided either directly, through cost-sharing initiatives to implement specific practices, or indirectly, via mechanisms such as crop insurance premium reductions, tax credits, or green financing supported by public bonds. Within

this context, the market prices of potential biodiversity credits could become a secondary consideration for farmers, resulting in an inefficient market for biodiversity financed by current and future taxpayers, as happened with the carbon credits market (Wongpiyabovorn et al., 2023).

However, market-based incentives are not always the most effective tools for driving behavioral change. For instance, when a large number of small transactions are involved, monitoring costs can become prohibitively high, making regulatory approaches more appropriate. Conversely, when the authority to establish and enforce regulations is highly fragmented across institutions, effective supervision and control may prove challenging, as has already been the case with carbon sequestration programs or markets (González-Ramírez et al., 2012).

Following a trajectory similar to the early stages of voluntary carbon markets more than 30 years ago, voluntary markets for biodiversity credits can grow. However, supply and demand uncertainties, lack of government-supported standards, and the absence of binding definition of the biodiversity-unit can generate uncertainty. (Wongpiyabovorn et al., 2023, 2021). Independent monitoring systems operated by third parties on a global and regional scale could provide up-to-date information to various actors and decision makers, helping to reduce potential price volatility and demand instability in these markets. Consequently, understanding farmers' preferences for different incentive mechanisms and monitoring structures is of critical importance.

2.2.3 Modeling risk attitudes towards changes in net returns

We analyze winegrowers' risk preferences by examining variations in net returns from entering a program to adopt sustainable practices.

Individual preferences and attitudes about risk play a crucial role in shaping decision-making processes (Dessart et al., 2019). When adopting sustainable practices creates uncertainty, farmers often require additional incentives to overcome these uncertainties (Chavas

and Nauges, 2020). However, the estimation of farmers' risk preferences relies on a wide range of elicitation methods (Iyer et al., 2020). Finger et al. (2023) highlight how preferences for risk can emerge and be structured as they are elicited, with different cognitive processes leading to different preferences.

While most of the empirical literature on eliciting farmers' risk preferences for adopting sustainable practices is based on a deterministic picture of the effect of risk attitudes, under the framework of Expected Utility Theory, a smaller number of studies (Ghadim et al., 2005) have considered the stochastic nature of the adoption process (Canales et al., 2024). By incorporating stochastic attributes within stated choice experiments, risk can be integrated into the Random Utility framework.

However, while the expected value of stochastic attributes captures the influence of uncertainty on preferences, it assumes the linearity of respondents' attitudes toward risk. Allais (1953), through his paradox, suggested that the designed probabilities provided in choice experiments are actually transformed by respondents. To account for this perceptual transformation of objective probabilities, a set of probability weighting functions has been introduced in the framework of Prospect Theory (Kahneman and Tversky, 1979).

To account for risk aversion and risk-seeking behavior, some studies of stated choice have incorporated elements of Expected Utility Theory and Prospect Theory into the Random Utility framework. This approach makes it possible to estimate decision makers' risk aversion and the marginal utility of stochastic attributes (Hensher et al., 2011). The non-linear weighting of probabilities helps explain the Allais paradox, which revealed violations of the normative principles of Expected Utility Theory.

In our study, we employ a nonlinear Extended Expected Utility framework (EEUT). This approach facilitates the estimation of three key parameters: the utility derived from net returns, farmers' subjective assessments of probabilities, and their risk preferences. By integrating these elements, our framework offers a comprehensive understanding of winegrowers'

decision-making processes under conditions of uncertainty.

2.3 Method and Data

2.3.1 Survey Implementation and Data

Between August and December 2024 questionnaire data were collected with a stated preference survey administered to companies managing vineyards and wineries across Italy. The survey was conducted by a polling company (Demetra) using a mixed-method approach that combined Computer-Assisted Telephone Interviewing (CATI) and Computer-Assisted Web Interviewing (CAWI). A total of 3,287 companies were contacted, of which 432 expressed an interest in participating. Out of these, 290 completed correctly the survey, resulting in a final response rate of 8.8%.

The characteristics of the wineries analyzed in this study are presented in Table 12. The sample of the companies' target respondents consists of 76.90% men with an average age of 46.37 years. 50.69% are college graduates and represent owners (53.79%) with more than 15 years of experience in the wine sector (64.14%).

The average farm size in our sample is 126.84 hectares (median = 23.5 hectares), significantly above the average farm size in the Italian wine sector (ISMEA-Istituto di Servizi per il Mercato Agricolo Alimentare, 2024). This because our study focuses on medium and large-scale farms, including entities such as cooperative wineries, which manage areas exceeding 1,000 ha of vineyards. More than 46% of sampled companies produce between 50,000 and 100,000 bottles per year or between 100,000 and 300,000, with an average of 43.69% of production being exported. This aligns with the national production structure, which allocates 44% of production to export markets (ISMEA-Istituto di Servizi per il Mercato Agricolo Alimentare, 2024). The gross sales value for the winegrowers in our sample is distributed as follows:

Table 7: Wineries Characteristics

Variable	**N**	**Mean**	**Std. Dev.**
Age	290	46.37	12.59
Male	290	76.90%	–
Education			
High school (or lower)	290	39.31%	–
Degree	290	50.69%	–
Postgraduate degree	290	10.00%	–
Role			
External consultant	290	3.45%	–
Employee	290	42.76%	–
Owner	290	53.79%	–
Work experience			
0-3 years	290	3.79%	–
3-8 years	290	15.17%	–
8-15 years	290	16.90%	–
More than 15 years	290	64.14%	–
Vineyard area	290	126.84	488.86
Production 2023 (bottles)			
less than 20,000	290	5.86%	–
20,000 - 50,000	290	15.52%	–
50,000 - 100,000	290	23.10%	–
100,000 - 300,000	290	23.79%	–
300,000 - 500,000	290	7.59%	–
500,000 - 1,000,000	290	9.66%	–
1,000,000 - 5,000,000	290	11.03%	–
more than 5,000,000	290	3.45%	–
Share of Production Exported	290	43.69	25.28
Gross sales value 2023 (Euro)			
less than 40,000	290	3.45%	–
40,000 - 100,000	290	5.17%	–
100,000 - 250,000	290	11.38%	–
250,000 - 500,000	290	17.59%	–
500,000 - 1,000,000	290	19.66%	–
1,000,000 - 5,000,000	290	26.21%	–
more than 5,000,000	290	16.55%	–
Employees			
0-2	290	28.62%	–
2-5	290	27.59%	–
5-10	290	22.07%	–
more than 10	290	21.72%	–
Organic farming	290	45.17%	–

a) 26.21% of farms fall within the €1 to €5 million sales category,

b) 19.66% within the €500,000 to €1 million category, and

c) 17.59% within the €250,000 to €500,000 category.

By contrast, farms with sales below €100,000, which account for approximately 20% of Italian wine-producing farms, are relatively under-represented, with only 8.62% of the farms in our sample.

Table 8 reports the adopted practices in the past five years, as reported in the winegrowers' interviews of our sample. Sustainable practices of No-herbicides (70.34%) and Spontaneous Inter-row Cover Crops (65.52%) appear to be the most widely adopted. The latter has the highest adoption rate in incentive programs (15.25%) being the practice with the lowest risk in terms of cost and potential damage to the vineyard.

Table 8: Adoption of sustainable practices in the past 5 years, adoption through incentive-based programs and percentage of area involved

Adoption type	**Spontaneous Inter-row Cover Crops**	**Pollinator-Friendly Inter-row Cover Crops**	**Minimum Soil Tillage**	**No Herbicides**	**Pesticides Banned at Flowering**
Prior adoption	65.52%	46.55%	20.00%	70.34%	59.66%
Prior adoption inside incentive programs	15.52%	4.48%	2.76%	9.66%	5.86%
Prior adoption outside incentive programs	50.00%	42.07%	17.24%	60.69%	53.79%
No-prior adoption	34.48%	53.45%	80.00%	29.66%	40.34%
Proportion of farm area involved					
1%–20%	2.11%	17.04%	6.90%	4.41%	4.62%
21%–40%	6.32%	9.63%	6.90%	1.96%	0.58%
41%–60%	13.68%	23.70%	15.52%	4.41%	1.73%
61%–80%	12.11%	9.63%	5.17%	4.90%	3.47%
81%–100%	65.79%	40.00%	65.52%	84.31%	89.60%

Among the least adopted practices, we found minimal soil tillage (20%) and pollinator-friendly inter-row cover crops (46.55%). 59.66% of winegrowers reported not using pesticides, but only 5.86% did so as part of an incentive program. Rather than through participation in an incentive-based program, prior adoption of these practices was primarily undertaken as a business and management decision. In our sample, many farmers did not implement these practices throughout their entire cultivation area, ensuring that a portion of their production remained risk-free.

2.3.2 Choice Experiment Design

The characteristics of the contract proposed in the discrete experiment design were selected to mimic the eco-schemes 2 and 5 proposed by Italy (Italy's CAP Strategic Plan, 2022) within the existing framework of CAP 2023-2027. The characteristics of the sustainable practices adoption contract and associated attribute levels in our choice experiment are presented in Table 13.

1. *Sustainable Conservation Practices*: Winemakers were required to adopt a package with a maximum of four different practices (inter-row spontaneous and pollinator-friendly cover crops practices were designated as mutually exclusive). The practices for each contract were presented as a bundled set of obligations, mimicking the structure of eco-schemes. For the experimental design, every practice was treated as dichotomous attributes.

2. *Payment*: annual incentive payment per hectare received for entering the program and implementing the specified package of sustainable practices.

3. *Incentives mechanism*: two types of incentive mechanisms were evaluated, a state-run program and a program involving the payment of biodiversity credits through a market-based system.

Table 9: Characteristics of the contract for adopting sustainable practices

Attribute	**Levels**
Inter-row spontaneous cover crops	1 if included, 0 otherwise
Inter-row pollinator-friendly cover crops	1 if included, 0 otherwise
Minimum soil tillage	1 if included, 0 otherwise
No-herbicides	1 if included, 0 otherwise
No-pesticides	1 if included, 0 otherwise
Payment (Euro/ha year)	150, 250, 500, 650, 800
Incentives mechanism	Cap-and-trade biodiversity credits=1; Public subsidies=0
Benefits	Brand=1; Vineyard health=0
Monitoring	Private=1; Public=0
Risk: impact on net returns (2 under levels)	
Average change on net returns over 5 years[a]	-5%, 0%, +5%
	-10%, 0%, +10%
	-15%, 0%, +15%
Probability of changes in net returns[b]	30% loss, 40% no change, 30% gain
	10% loss, 80% no change, 10% gain
	5% loss, 60% no change, 35% gain
	35% loss, 60% no change, 5% gain

Note: [a] Each row in the Average change on net returns over 5 years under level represents a net return distribution in which is possible to have losses (negative values), no change in net returns (0) or gains (positive values).
[b] Each row in the Probability of changes in net returns under level represents the probability of loss, no change, and gain occurring for the associated net return distribution.

4. *Benefits*: we assessed the extent to which preferences were influenced by market-related economic factors, such as access to niche markets and brand enhancement, or by farm-related assets, such as vineyard health and productivity.

5. *Monitoring*: one of the key factors limiting adoption rates is the control and measurement of outcomes (Calliera et al., 2021). We evaluated preferences for a monitoring system managed by private entities or public institutions.

6. *Program Risk*: the implementation of the sustainable practices may elevate income risk due to fluctuations in production costs and vineyard yields. The risk associated with contractual agreements was incorporated into the experimental design by presenting a probability distribution of potential changes in average net farm income over five years. Respondents were provided with a discrete symmetric probability distribution outlining potential loss, no change, or a gain in net returns under the adoption of practices (e.g. 5% loss, no change, or a 5% gain). The probability of each outcome was modeled using four distinct probability distributions linked to potential changes in net returns. Two of these distributions were symmetric, with equal probabilities of losses and gains.

   (a) The first distribution (30% probability of loss, 40% probability of no change, 30% probability of gain) represented a scenario with *high uncertainty*, where the likelihood of all three outcomes was *nearly equal*.

   (b) The second distribution (10% probability of loss, 80% probability of no change, 10% probability of gain) depicted a situation where net returns were highly likely to remain unchanged, with *low and equal probabilities of losses or gains*.

   (c) The third distribution (5% probability of loss, 60% probability of no change, 35% probability of gain) was *skewed toward gains*, while the fourth distribution (35% probability of loss, 60% probability of no change, 5% probability of gain) was *skewed toward losses*.

In designing the discrete choice experiment, we initially developed an optimal orthogonal-in-the-differences design. This was used in a pilot study involving a sample of 40 winegrowers, following the design principles outlined by (Street et al., 2001, 2005). Subsequently, we used the parameters obtained from the pilot study to obtain a Bayesian average D-error minimizing efficient design. Design simulations were run with 500 Halton draws producing an average D-error of 0.143, on a design with 192 choice tasks (Ferrini and Scarpa, 2007a; Scarpa and Rose, 2008; Bliemer and Rose, 2010, 2011; Rose and Bliemer, 2013a). The 192 choice sets were orthogonally divided into 24 blocks, each consisting of 8 tasks.

Every winegrower evaluated 8 contract scenarios. Each scenario included one incentive-based program and a status quo option, giving rise to a binary response to ensure incentive compatibility (Carson and Groves, 2007; Collins and Vossler, 2009; Czajkowski et al., 2017a; Canessa et al., 2023). The description of the contract attributes presented to winegrowers was delivered in multiple formats: it was provided in written form before the choice experiment, explained orally during the CATI survey's presentation phase, and integrated into the online choice cards as informational text links accessible via an "i" icon for each attribute level.

2.3.3 Modeling Choices Under Uncertainty and Risk Preferences

We assume that in the voluntary adoption of an incentive-based program for sustainable practices wine producers act as expected utility maximizers, and in doing so they are influenced by their risk preferences.

The expected net return for farmer n under their production system in the status quo is denoted by π_{nq}, while π_{nj} denote the expected net return under the proposed incentive-based program j, excluding incentive payments.

The uncertainties associated with all stochastic factors, such as market conditions, weather variables, and agronomic practices, make net returns also stochastic. This happens both under the status quo— with an associated variance $\sigma^2_{\pi q}$—and under the program—with a

corresponding variance $\sigma^2_{\pi j}$.

We assume that the expected utility of winegrower n^{th} from participating in program j is a function of the utility derived from the attributes of the program proposed in the contract, denoted by X_j, and the stochastic net returns $\pi_{nj}(\sigma^2_{\pi j})$. Specifically, the deterministic component of n 's expected utility adopting program j is expressed as

$$V_{nj} = [X_j, F(\pi_{nj}(\sigma^2_{\pi j}))], \tag{3}$$

Using the framework of Prospect Theory (Kahneman and Tversky, 1979) and following Hensher et al. (2015), the valuation of the stochastic returns under sustainable practices from the adoption of program j is incorporated with a nonlinear relationship.

This approach explicitly recognizes that respondents' perception of "objective" probabilities often results in an either over- or under-weighting of those probabilities. We have selected the functional form originally proposed by Tversky and Kahneman (1992) (Eq.4) based on a single parameter γ, as well as the two-parameter form (Eq. 5) proposed by Goldstein and Einhorn (1987) based on γ and τ:

$$w(p_0) = \frac{p_0^\gamma}{[p_0^\gamma + (1-p_0)^\gamma]^{\frac{1}{\gamma}}} \tag{4}$$

$$w(p_0) = \frac{\tau p_0^\gamma}{\tau p_0^\gamma + (1-p_0)^\gamma}, \tag{5}$$

where, $w(p_0)$ is a nonlinear probability weighting function, where p_0 represents the probability associated with the outcome of changes in net returns, and γ and τ are the probability weighting parameters.

Specifically, $\gamma > 0$ represents the degree of curvature, and $\tau > 0$ determines the elevation of the weighting function. Note that γ decreases, there is greater diminishing sensitivity to probabilities near the boundaries of 0 and 1. Eq. 4 is a single-parameter inverse S-shaped

weighting function with *over-weighting* of low probabilities and *under-weighting* of high probabilities for values of $0 < \gamma < 1$. Eq. 5 is a two-parameter form where $\tau > 0$ controls the elevation of the inflection point where the function goes from concave to convex (or convex to concave) (Hensher et al., 2011).

To model risk attitudes with a nonlinear specification of the utility function, we use the constant relative risk aversion (CRRA) specification (Blanchard, 1989). Assuming that winegrowers exhibit risk aversion, the utility function is concave with respect to net returns x_m . Specifically, the individual utility function can be defined as $v_n = x_m^{1-\alpha_n}/1 - \alpha_n$, where α_n represents the individual coefficient of risk aversion (Pratt, 1964).

Thus, an attribute-specific extended expected utility term is included in the indirect utility function of each respondent,

$$EEUT_n = \frac{\Sigma w_n(p_m)\pi_m^{1-\alpha_n}}{1-\alpha_n} \tag{6}$$

This simultaneously accounts for the stochastic nature of farmers' net returns and risk preferences.

2.3.4 Empirical Model and Marginal Willingness to Accept Estimation

The empirical application of our model focuses on estimating the determinants of the adoption of sustainable practices in incentive-based programs, the risk associated with expected net returns, and the derivation of measures of WTA. The EEUT functional form in Eq. 7 is embedded in the utility function in Eq. 8. This, assuming random utility maximization, introduces nonlinearity in a value specification of net returns conditional on the assumed probability weighting $w(p)$ (Hensher et al., 2011). The specific equations are as follows:

$$
\begin{aligned}
EEUT_{njt} =& w_n(p^1_{njt})\frac{(\pi_0 - \Delta\pi_{loss})^{1-\alpha_n}}{(1-\alpha_n)} + \\
& w_n(p^2_{njt})\frac{(\pi_0)^{1-\alpha_n}}{(1-\alpha_n)} + \\
& w_n(p^3_{njt})\frac{(\pi_0 + \Delta\pi_{gain})^{1-\alpha_n}}{(1-\alpha_n)}
\end{aligned} \tag{7}
$$

$$
\begin{aligned}
U_{njt} =& ASC_{program} + \beta^{€} Pay_{njt} + \sum_k \beta^k X_{ijtk} + \beta^{EUT}_n EEUT_{njt} + \\
& \sum_p \beta^p_n Practice_{njtp} + \sum_p \theta^p Practice_{njtp} PA_{njtp} + \varepsilon_{njt},
\end{aligned} \tag{8}
$$

The term $ASC_{program}$ represents an alternative-specific constant that captures the utility associated with participating in the program. The variable $EEUT$ denotes the attribute-specific extended expected utility, while β_{EUT} represents the expected marginal utility derived from the anticipated net returns under risk, taking into account the winemaker's risk preferences and subjective utility assessment. The function $w(p)$ is a nonlinear probability weighting function, defined by Equations 4 or 5.

The expression in Equation 7 represents the individual probability-weighted average utility, assuming a general power specification, across three possible outcomes in terms of net returns. Here, π_0 corresponds to the net returns under the status quo (i.e., $\pi_0 = 100\%$ of the baseline net returns), $\Delta\pi_{loss}$ denotes a percentage decrease in net returns, and $\Delta\pi_{gain}$ represents a potential percentage increase in net returns. In this framework, α_n signifies the risk aversion coefficient of an individual winegrower n.

To account for unobserved heterogeneity in respondents' risk-taking behavior and willingness to adopt sustainable practices, we model α_n as a random parameter, such that $\alpha_n = \alpha_0 + \sigma_\alpha z_n$, where $z_n \sim N(0,1)$. Similarly, subjective probability assessments are likely to vary randomly across individuals. Accordingly, we assume that the parameters γ and τ are also stochastic, following the specifications $\gamma_n = \gamma_0 + \sigma_\gamma z_n$ and $\tau_n = \tau_0 + \sigma_\tau z_n$, where all $z_n \sim N(0,1)$.

The variable $Practice$ is a binary indicator that takes the value of one if the sustainable program mandates the adoption of a given practice $p = \{SPO, BEE, TIL, HER, PES\}$. Farmers exhibit unobserved heterogeneity due to latent factors influencing their adoption decisions regarding various practices. To model this, we assume that the respondent-specific parameter for each sustainable practice p follows the specification $\beta_{np} = \beta_{p0} + \sigma_p z_n$, where $z_n \sim N(0, 1)$. Given our sample of surveyed winegrowers, many had already adopted certain conservation practices (see Table 8). Prior adoption likely alters the marginal expected utility derived from incorporating a practice into the program. To account for this effect, we introduce indicators of prior adoption, denoted as PA. These binary adoption variables interact with the binary practice attributes in the expected utility function, adjusting for preference heterogeneity and capturing potential additionality associated with conservation contracts.

Conservation behavior extends beyond the adoption of specific practices and encompasses broader program components and corporate benefits. Other contract attributes, represented by X_k, include a binary indicator that equals one if the program offers an authorization payment through a biodiversity market and zero (the baseline) if it provides a direct government payment under a state-administered scheme.

Additional attributes include indicators of farm-level benefits, which may be associated with access to market niches and brand enhancement (coded as one) or vineyard health (coded as zero, the baseline). Moreover, the monitoring and control system is represented by a binary variable, taking a value of one if managed by private entities and zero if overseen by public institutions.

We estimated the model specified in Equation 8 using two probability weighting specifications outlined in Equations 4 and 5, along with a third specification without probability weighting, in line with standard expected utility theory. The models were estimated using nonlinear random parameter logit regressions with 1,000 modified Latin hypercube sampling

draws, implemented in Apollo using R (Hess and Palma, 2019; Hess et al., 2006).

The mean willingness to accept (WTA) for attribute k is calculated as the ratio of the marginal utility of attribute k to the incentive payment, given by $WTA_n^k = -(\partial V_n/\partial x_k)/(\partial V_n/\partial pay)$. For attributes entering the indirect utility function in a linear form, the WTA simplifies to $WTA_n^k = -\frac{\beta_n^k}{\beta^{€}}$, where β_n^k is the parameter associated with attribute k, and $\beta^{€}$ represents the monetary incentive payment parameter.

For each sustainable practice p, where heterogeneity in the mean of the practice's random parameters is incorporated through interactions with prior adoption indicators, the WTA is estimated as $WTA_n^p = -\frac{\beta_n^p+\theta^p}{\beta^{€}}$. Moreover, the WTA is estimated conditionally on prior adoption status. If $PA = 1$, then $WTA_n^p = -\frac{\beta_n^p+\theta^p}{\beta^{€}}$, which quantifies the level of incentive—if positive—required to continue participation in the program. For winegrowers who have not previously adopted practice p, where $PA = 0$, the WTA is given by $WTA_n^p = -\frac{\beta_n^p}{\beta^{€}}$. In this case, WTA captures the necessary monetary incentive for a program—whether public or market-based—to enhance additionality.

In summary, the WTA for non-adopters reflects the incentive required to encourage the adoption of a conservation practice, motivating them to engage in sustainable initiatives. Conversely, the WTA for adopters estimates the incentive needed to sustain or intensify their engagement within the program.

2.4 Results

Table 10 reports the results of the nonlinear random parameter logit model. The models with two-parameter and one-parameter probability weighting functions yield similar parameter estimates in both sign and magnitude. Robustness is further supported by the consistency with the model excluding probability weights. Behaviorally, the two-parameter weighting function better captures decision-making under risk than the one-parameter version (Hensher et al., 2011). Separately representing curvature and elevation—two logically independent

components (Gonzalez and Wu, 1999)—provides a plausible account of discriminability, attractiveness, and the observed probabilistic risk attitude. Thus, the discussion will primarily focus on the results obtained from the model estimation using the Goldstein and Einhorn probability weighting function. The alternative-specific constant for the program is negative and statistically significant, while the payment coefficient is positive and statistically significant. Consistent with previous literature, farmers are more willing to participate in a sustainable practice adoption program as the level of monetary incentives increases.

2.4.1 Perceptual conditioning and risk attitude toward net income fluctuation

Our findings indicate that the parameters of the probability weighting function deviate statistically from one in a specific direction ($\gamma < 1$), signifying an over-weighting of low probabilities and an under-weighting of high probabilities. This result is consistent with previous empirical applications (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992; Canales et al., 2024). On average, the estimated parameter values suggest that subjective transformations of probabilities into decision weights are minimal. Figure 2 illustrates this result by showing the deviation from the linear specification of the probability weighting function at the mean, maximum, and minimum values of γ and τ.

The perceptual conditioning of the probabilities in our sample does not differ with a high magnitude from the absence of probability weighting $w(p) = p$. This is partly because the probability weighting parameters are treated as random to account for sample heterogeneity. At the extremes of individual-specific parameter distributions, respondents may substantially underweight or overweight probabilities. The distributions of the parameters γ and τ are presented in Figure 3.

Furthermore, the mean of the distribution of the risk coefficient (α_0) is statistically different from zero, as is its standard deviation, indicating heterogeneity in risk preferences among the sampled population. The estimated average risk attitude parameter has a value of 0.461,

Table 10: Random Parameters Logit results for different probability weights

Variables	**Goldstein & Einhorn Parameter (St. Err.)**	**Tversky & Kahneman Parameter (St. Err.)**	**No Prob. Weight Parameter (St. Err.)**
Random Parameters			
α_0	0.461*** (0.103)	0.455*** (0.043)	0.453*** (0.092)
σ_α	0.050*** (0.011)	0.051*** (0.008)	0.051*** (0.010)
γ_0	0.995*** (0.050)	0.987*** (0.035)	
σ_γ	0.055** (0.023)	−0.080 (0.059)	
τ_0	1.003*** (0.051)		
σ_τ	−0.001 (0.012)		
μ_{SPO}	−0.425 (0.358)	−0.410 (0.356)	−0.413 (0.350)
σ_{SPO}	1.169*** (0.390)	1.123*** (0.339)	1.141*** (0.314)
μ_{BEE}	−0.412 (0.301)	−0.446 (0.312)	−0.437 (0.308)
σ_{BEE}	1.401*** (0.372)	1.347*** (0.375)	1.312*** (0.345)
μ_{TIL}	−1.671*** (0.262)	−1.680*** (0.268)	−1.645*** (0.255)
σ_{TIL}	1.601*** (0.276)	1.565*** (0.312)	1.503*** (0.261)
μ_{HER}	−1.566*** (0.420)	−1.643*** (0.453)	−1.591*** (0.416)
σ_{HER}	1.050** (0.433)	1.120*** (0.385)	1.089*** (0.365)
μ_{PES}	−1.073*** (0.295)	−1.105*** (0.293)	−1.091*** (0.282)
σ_{PES}	1.269*** (0.321)	1.093*** (0.241)	1.075*** (0.227)
Non-random Parameters			
ASC	−25.315*** (2.638)	−24.395*** (2.302)	−24.519*** (2.340)
Payment	3.061*** (0.469)	3.050*** (0.461)	3.027*** (0.455)
Mechanism[a]	0.311* (0.167)	0.298* (0.162)	0.291* (0.161)
Benefit[b]	−0.076 (0.163)	−0.086 (0.156)	−0.085 (0.155)
Monitoring[c]	0.328* (0.168)	0.334** (0.167)	0.337** (0.166)
β_{EUT}	1.086*** (0.195)	1.030*** (0.045)	1.032*** (0.166)
SPO^{PA}	0.456 (0.425)	0.436 (0.416)	0.434 (0.409)
BEE^{PA}	0.393 (0.376)	0.455 (0.384)	0.442 (0.376)
TIL^{PA}	0.804* (0.477)	0.827* (0.451)	0.804* (0.453)
HER^{PA}	1.728*** (0.451)	1.785*** (0.481)	1.717*** (0.440)
PES^{PA}	0.906*** (0.349)	0.966*** (0.345)	0.959*** (0.338)
Log likelihood	−1104.73	−1105.33	−1105.66
AIC	2263.46	2260.66	2257.33
N. observations	2320	2320	2320

Note: Sustainable practices are spontaneous inter-row cover crops (SPO), pollinator-friendly inter-row cover crops (BEE), minimal soil tillage (TIL), herbicide-free practices (HER), and pesticide-free practices during flowering (PES). ^{PA} Prior adopted practices.

[a]The incentive mechanism is a biodiversity credit payment through a cap-and-trade system, where a state-led program is the baseline.

[b]The benefit is an improvement of the brand, where the improvement of the vineyard's health is the baseline.

[c]The monitoring system is private, where a public system is the baseline.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

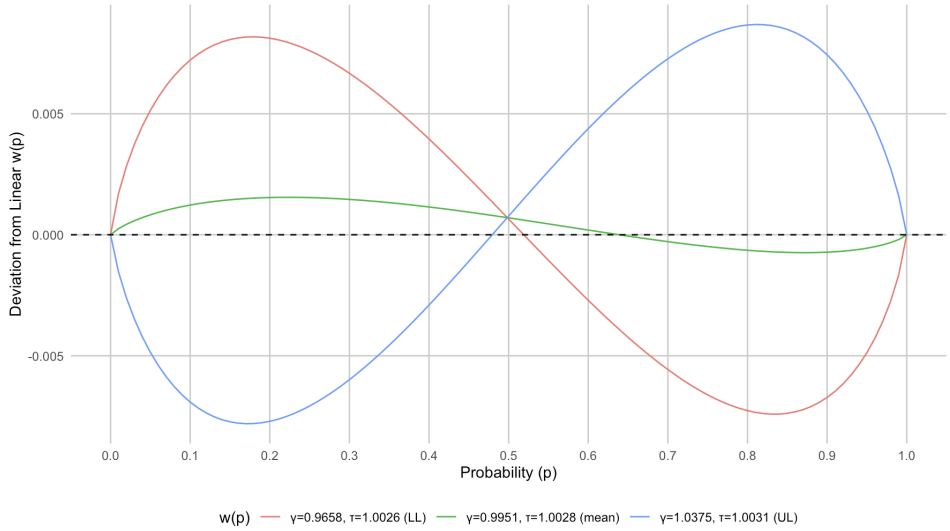
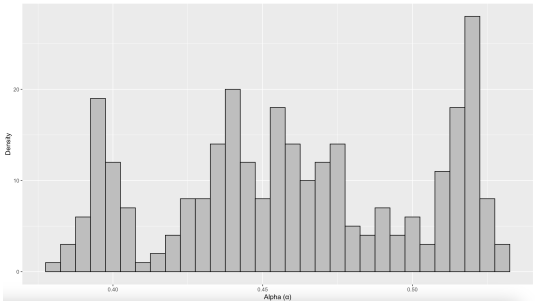


Figure 2: Deviation from the linear specification of the probability weighting function at the mean, maximum, and minimum values of γ and τ.

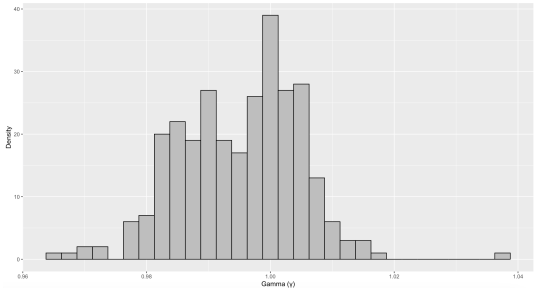
suggesting that farmers in our sample are risk-averse (i.e., $\alpha > 0$). This aligns with findings from prior studies (Chavas and Nauges, 2020). It is interesting to note that, in the conditional distribution of the risk aversion parameter at the disaggregated level, all respondents exhibit risk aversion ($a > 0$) (Fig. 3a). This finding also explains the general absence of risk-seeking behavior when winegrowers make potentially risky decisions related to agronomic practices. Additionally, the extended utility term parameter, specific to the net returns attribute, is positive and statistically significant, underscoring its influence on decision-making.

The conditional mean of the attribute-specific parameter EEUT and the Goldstein and Einhorn probability weighting function were used to estimate the risk premium. Variations in net returns associated with the adoption of sustainable practices under the program require additional income compensation to make a risk-averse farmer indifferent to risk to enter in a program. This compensation represents the risk premium, estimated through the calculation of the certainty equivalent, defined as $E\hat{E}UT^{-1} = E(\pi) - p$, based on the relationship $EEUT = U[E(\pi) - \text{Risk Premium}]$.

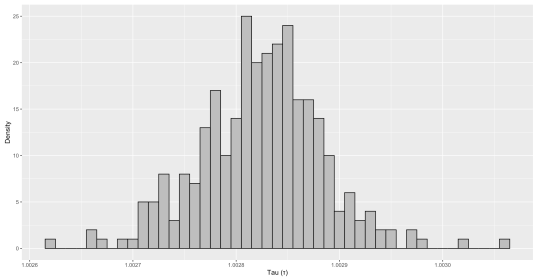
The individual distribution of the risk premium (3d), representing the individual cost



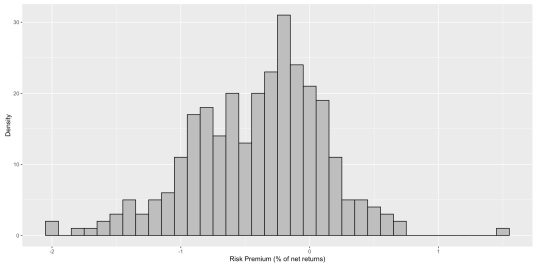
(a) Risk aversion parameter α



(b) Probability weight parameter γ



(c) Probability weight parameter τ



(d) Risk premium

Figure 3: Distributions of risk attitude parameters and risk premium

of bearing risk, reveals sample heterogeneity, with negative values observed for 80.34% of respondents. This indicates that most winegrowers are willing to pay to enter the program if doing so ensures an increase in net returns, with a mean of -0.40% (-1.40% to 0.59%, 95% CI). This estimate is influenced by farmers' subjective perception of how the specific practices affect net returns, likely offering a representation of the actual impact of incentive-based program adoption on individual farm performance.

2.4.2 Market-based programs and private monitoring system

The coefficients associated with the incentive mechanism of the biodiversity credit-based program and the privately managed monitoring and control system were positive and statistically significant. This suggests a higher likelihood of adoption for the same incentive level when the mechanism involves a biodiversity credit mechanism operating through a market with a private certification scheme.

The mean WTA estimate for the biodiversity market program was -0.102 thousand €/ha (-0.211 to -0.008 thousand €/ha, 95% CI) (Table 11). The mean WTA estimate for the private monitoring and control system was -0.107 thousand €/ha (-0.215 to -0.001 thousand €/ha, 95% CI). In other words, for programs with similar features, winegrowers would be willing to pay 102 €/ha per year to enroll in a biodiversity credit program rather than a state or regional program. They would also be willing to pay 107 €/ha per year for a private certification scheme compared to a public control system.

Biodiversity credits represent a mechanism highlighted in Target 19 of the 2022 Global Biodiversity Framework, designed to channel private sector investments into biodiversity and ensure that these funds deliver verifiable conservation and restoration outcomes (Global Biodiversity Framework, 2022). The observed preference among winegrowers can be interpreted on multiple levels. First, to enhance their brand image and marketing strategies, wine producers may target niche markets—a key driver for a sustainable agri-food system (Olagunju et al., 2025). Second, after assessing and attempting to reduce their environmental impact, wineries could attract potential investors from other sectors interested in indirectly safeguarding their primary business asset, natural capital. Finally, for cooperative organizations collectively managing larger areas, regulated biodiversity credits market could serve as an important supply chain monitoring tool.

Additionally, these findings indicate that winegrowers, while exhibiting risk aversion in terms of environmental asset management, appear willing to accept the inherent risk associated with performance-based payments—contrary to the behavior generally observed among farmers in the context of carbon credits (Ribaudo et al., 2017). Despite the absence of clear legislation and limited awareness regarding what constitutes a high-quality biodiversity credit, and which regulatory mechanisms could stabilize the volatility of environmental credit prices (Wongpiyabovorn et al., 2023), winegrowers perceive the potential revenue increase associated with this mechanism as more attractive than a guaranteed payment through a

Table 11: Mean Willingness to Accept (WTA) for Program Attributes in (,000 €/ha) Across Models Estimated Using Different Probability Weights

Attribute	**Goldstein & Einhorn WTA (Std.Error) [95% CI]**	**Tversky & Kahneman WTA (Std.Error) [95% CI]**	**No Prob. Weight WTA (Std.Error) [95% CI]**
SPO	0.139 (0.117)	0.135 (0.114)	0.136 (0.113)
	[−0.089, 0.368]	[−0.089, 0.358]	[−0.085, 0.358]
BEE	0.136 (0.097)	0.146 (0.098)	0.144 (0.097)
	[−0.053, 0.325]	[−0.045, 0.337]	[−0.046, 0.335]
TIL	0.551 (0.107)	0.551 (0.104)	0.543 (0.101)
	[0.342, 0.759]	[0.347, 0.755]	[0.345, 0.742]
HER	0.529 (0.130)	0.539 (0.134)	0.526 (0.129)
	[0.273, 0.784]	[0.275, 0.802]	[0.273, 0.778]
PES	0.359 (0.105)	0.362 (0.103)	0.360 (0.102)
	[0.152, 0.565]	[0.160, 0.565]	[0.160, 0.560]
SPO^{PA}	−0.009 (0.177)	−0.008 (0.174)	−0.007 (0.173)
	[−0.357, 0.339]	[−0.350, 0.333]	[−0.347, 0.332]
BEE^{PA}	0.004 (0.157)	−0.003 (0.158)	−0.002 (0.157)
	[−0.303, 0.310]	[−0.312, 0.306]	[−0.309, 0.306]
TIL^{PA}	0.286 (0.182)	0.280 (0.176)	0.278 (0.175)
	[−0.070, 0.642]	[−0.066, 0.625]	[−0.066, 0.621]
HER^{PA}	−0.046 (0.172)	−0.047 (0.178)	−0.042 (0.171)
	[−0.383, 0.291]	[−0.396, 0.303]	[−0.376, 0.293]
PES^{PA}	0.051 (0.151)	0.046 (0.148)	0.043 (0.146)
	[−0.246, 0.347]	[−0.244, 0.335]	[−0.243, 0.330]
Mechanism[a]	−0.097 (0.058)	−0.098 (0.057)	−0.096 (0.057)
	[−0.210, 0.016]	[−0.210, 0.014]	[−0.208, 0.015]
Benefit[b]	0.028 (0.054)	0.028 (0.054)	0.028 (0.054)
	[−0.079, 0.134]	[−0.077, 0.134]	[−0.077, 0.133]
Monitoring[c]	−0.111 (0.057)	−0.110 (0.057)	−0.007 (0.173)
	[−0.224, 0.001]	[−0.221, 0.002]	[−0.347, 0.332]

Note: Sustainable practices are spontaneous inter-row cover crops (SPO), pollinator-friendly inter-row cover crops (BEE), minimal soil tillage (TIL), herbicide-free practices (HER), and pesticide-free practices during flowering (PES). ^{PA} Prior adopted practices.

[a]The incentive mechanism is a biodiversity credit payment through a cap-and-trade system, where a state-led program is the baseline.

[b]The benefit is an improvement of the brand, where the improvement of the vineyard's health is the baseline.

[c]The monitoring system is private, where a public system is the baseline.

state-based incentive scheme.

Evidence of a market-oriented attitude is further supported by the preference for a privately managed monitoring and control system. Winegrowers in our sample perceive greater value in independent third-party audits, as reflected in their WTP for such a system.

2.4.3 Payments for adopting sustainable practices in the vineyard

The parameters associated with sustainable practices related to minimal soil tillage and non-use of herbicides and pesticides are negative and statistically significant, while the parameters associated with the interaction between these practices and their previous adoption are positive (see Table 10). These results suggest that previous adoption plays a crucial role in influencing farmers' enrollment in sustainable programs. Specifically, farmers who have already implemented the prescribed measures demonstrate a higher likelihood of participating in such programs (Canales et al., 2024).

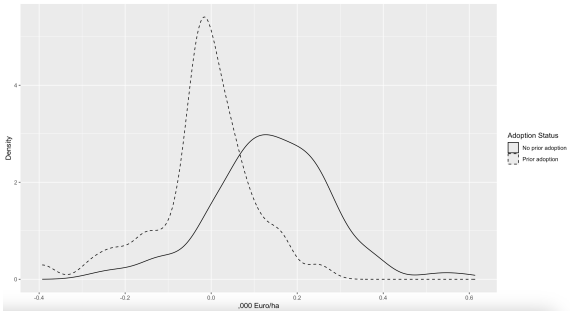
The results in Table 11 represent the incentive payment per hectare required by winegrowers to induce the adoption of these practices (non-adopters) or to encourage the continuation of adoption (adopters). Several factors may influence the WTA for conservation practices, including site-specific soil and climate conditions, production protocols that in some cases overlap with eco-schemes, implementation and maintenance costs, and the risk associated with potential yield losses. The parameters associated with inter-row cover cropping practices (both spontaneous and pollinator-friendly) were not statistically significant. This result may be explained by the fact that, compared to other practices resembling eco-schemes in our experiment, these practices are not associated with agronomic production risks that could affect product quality (Muscas et al., 2017), and winegrowers do not need an incentive that covers the risk.

The estimated WTA for the adoption of minimum soil tillage was 0.546 thousand €/ha (0.356–0.736 thousand €/ha, 95% CI). The incentive required to induce adoption can be

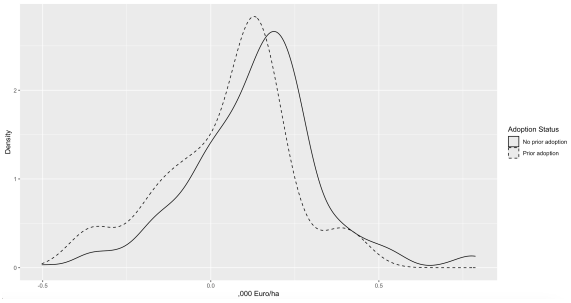
attributed to the increased labor costs associated with this practice compared to a mechanized approach, which exerts a greater impact on the soil. Even among those who had already adopted the practice, the WTA remained positive, though lower, at 0.283 thousand €/ha (0.003–0.563 thousand €/ha, 95% CI). Similarly, the estimated WTA to refrain from pesticide use during flowering was 0.351 thousand €/ha (0.150–0.551 thousand €/ha, 95% CI) for non-adopters and 0.055 thousand €/ha (-0.099–0.207 thousand €/ha, 95% CI) for adopters. For both practices, the cost associated with continuity is lower than that required to induce initial adoption. For winegrowers, participation in a program that inherently involves certain restrictions leads to a general preference for receiving a maintenance payment (Canales et al., 2024). The distributions of conditional WTA for the sustainable practices assessed are shown in Figure 4.

For inter-row cover crops, implementation costs and returns in terms of vineyard benefits vary widely across different operations and cover crop species, and we expect variability in the level of incentive required (Bergtold et al., 2019). In fact, past state programs have been decisive in increasing the adoption of cover crops, not only in vineyards. Although the average WTA for producers who have already adopted cover crops is not statistically different from zero, incentive payments to continue using spontaneous cover cropping practices amount to -0.10 thousand €/ha. Thus, there is a WTP for winegrowers using cover crops who have experienced benefits that offset the cost of managing this practice. This and other studies highlight the importance of communicating the agronomic and economic benefits when promoting the adoption of conservation practices.

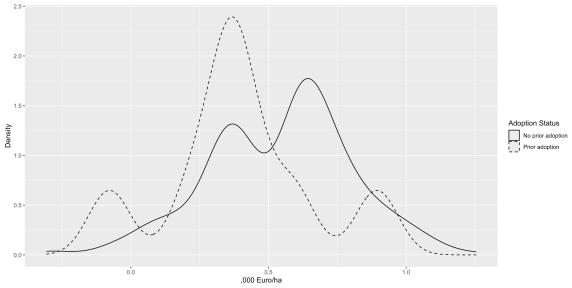
As our results indicate, prior adoption plays a role in farmers' WTA for the conservation practices required under a conservation program. Higher adoption rates and greater experience with sustainable practices can reduce uncertainty about the costs and benefits associated with these practices (4). The distribution is narrower for inter-row spontaneous cover cropping and herbicide non-use, compared to the distribution for pesticide non-use, which exhibits lower



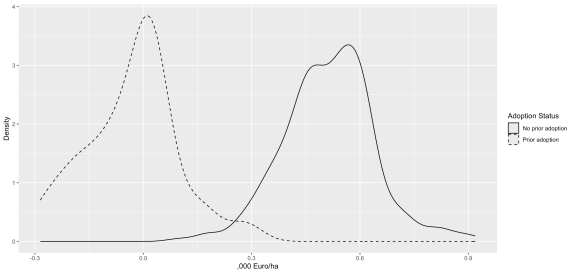
(a) Inter-row spontaneous cover crops



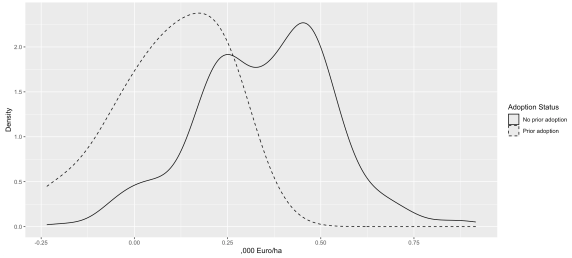
(b) Inter-row pollinator-friendly cover crops



(c) Minimum soil tillage



(d) No-herbicides



(e) No-pesticides during flowering

Figure 4: Distribution of conditional willingness to accept (WTA) estimates for sustainable practices. WTA estimates are based on individual specific parameter means

adoption rates and a wider distribution, indicative of greater uncertainty.

Incentive payments are an important factor in joining programs to adopt sustainable practices (Antle and Diagana, 2003; Cooper and Keim, 1996). Although not the only reason, an unattractive incentive turns out to be an important barrier to adoption. Our results show that the ecosystem services provided by the practices examined are valued by winegrowers with higher values than the incentives proposed in the eco-schemes (Italy's CAP Strategic Plan, 2022). This may explain the low adoption rate recorded to date.

2.5 Conclusions

Within the framework of stated choice modeling, we analyzed the incentives needed to encourage the adoption of sustainable practices, aligned with the eco-schemes under the first pillar of the 2023-2027 CAP. We compared winegrowers' preferences for a hypothetical biodiversity market with an incentive mechanism based on state subsidies and examined the impact of a monitoring and control system managed by independent third parties versus public management. We also explored winegrowers' willingness to adopt sustainable practices, considering the stochastic nature of net returns and the distribution of potential outcomes linked to the program's features. We used a nonlinear random parameter logit for the analysis, incorporating a nonlinear utility component based on winegrowers' subjective evaluation of probabilistic outcomes through a probability weighting function. Variations in winegrowers' risk aversion and required risk premium show as risk and uncertainty play a role in decisions about participating in eco-schemes.

The findings suggest that winegrowers who have already adopted sustainable practices require lower incentives than those needed for initial adoption, underscoring the higher costs of additionality compared to maintaining existing practices. For some practices, like No-herbicides, current adopters are willing to pay to continue their implementation. This reveals two key points: first, experience and familiarity with sustainable practices increase perceived

benefits relative to adoption costs; second, the eco-schemes structure, designed as a bridge between conditionality and more advanced ecological requirements, in some cases risk to fund sustainable practices that are already common in some regions, leading to inefficient use of financial resources.

For other practices, like Minimum soil tillage and No-pesticides during flowering, even prior adopters still need incentives, though at lower levels compared to non-adopters. This suggests that eco-schemes offering modest incentives for those not yet engaging in sustainable practices may actually attract more established adopters, resulting in limited additional environmental benefits. It is also worth noting that the levels of WTA vary depending on the production region and territorial characteristics as evidenced by the variability in individual level distribution (Sawadgo and Plastina, 2022).

This study also revealed that winegrowers prefer an incentive mechanism based on the biodiversity credit market. This is a significant finding. If the incentives currently offered are insufficient to achieve large-scale environmental benefits, establishing a sector-specific regulatory system for this market could enable self-management of natural capital. It is important to note that the wine sector is the least dependent on subsidies within agriculture due to the characteristics of its market. Our results show that winegrowers are willing to pay to offset the risk associated with adopting certain practices (e.g., the No-pesticide approach potentially poses a high risk to productivity) and to participate in a market mechanism that ensures increased net returns. In other words, they are ready to take on business risks, provided there is a regulated system and, importantly, that this system is monitored and controlled by independent third parties.

Despite these insights, this study has clear limitations. The generalizability of our results is constrained by sample characteristics. Moreover, the design of our stated choice experiment presents challenges in distinguishing whether farmers assessed the contract's risk component based on a comparison between a risky contract and a risk-free status quo. Future research

should address these concerns.

Despite its limitations, this study offers important insights into the mechanisms influencing participation in incentive-based programs like eco-schemes for a specific sector. On a broader scale, the provision of ecosystem services linked to sustainable practices appears to be performance-based, highlighting the need for further investigation into the marginal costs and benefits of providing such services within context-specific frameworks. Future developments of this research should consider the spatial dimension on a smaller (regional) scale to achieve more efficient resource allocation, possibly through collective management approaches.

3 Asset Integration and Risk Attitudes: Further Evidence from a Choice Experiment on the Adoption of Sustainable Agricultural Practices

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Abstract

When evaluating business options that entail a certain degree of risk in experimental settings, such as adopting sustainable practices within incentive-based programs, do farmers integrate their pre-existing wealth with the potential effects on future net returns? In this study, we implemented a choice experiment designed to measure risk preferences and the subjective probability weight assigned to the economic impacts of adopting sustainable practices within the framework of the Eco-schemes in the European Union's Common Agricultural Policy. We combined experimental data with farm-level information on asset holdings to assess whether decisions were made by incorporating pre-existing wealth or by evaluating economic outcomes in isolation. We examined the impact of these factors using a nonlinear random parameter logit regression that incorporated a nonlinear expected utility component that took into account both farmers' subjective assessments of probabilistic outcomes using a probability weighting function and the extent to which individual assets was integrated

into choices. The results indicate that, consistent with previous experimental findings, farmers tend to assess the experimental impacts on net returns without systematically factoring in their initial level of farm wealth. The implicit attitudes toward risk derived from the estimation of these specifications confirm the common assumption of narrow framing in risk aversion experiments, leaving open the discussion on the external validity of experiments in the agricultural sector.

Keywords: Asset integration; Sustainable practices adoption; Narrow framing; Choice under uncertainty; Non-linear utility

JEL Classifications: C83, C25, Q17.

3.1 Introduction

The debate on decision-making under risk and uncertainty has renewed interest in how the utility function is defined with respect to event outcomes. In experimental settings involving choice, lotteries are frequently employed to assess risk preferences, typically presenting participants with options between two distinct probability distributions over prizes. In the majority of instances, these prizes are considered the sole variable of the utility function, thereby implicitly adopting a narrow framing in which the decision-maker evaluates gains independently of their broader economic context (Gu et al., 2025).

However, the axioms of Expected Utility Theory (EUT) do not impose a specific form for defining final wealth as the outcome of a decision (Andersen et al., 2018), allowing for both approaches—those based solely on experimental payoffs and those define the utility function over the decision maker's final monetary outcome. When, as in our case, the experimental evaluation is closely tied to a concrete business context—such as the adoption of sustainable practices within incentive-based programs—the use of small-stakes lotteries could lead to

implausible implications about risk preferences (Rabin, 2000).

The probable economic impact of implementing sustainable practices is inherently stochastic, influenced by multiple factors, and therefore requires an understanding of the subjective weight that farmers assign to the probabilities of various scenarios occurring. Consequently, the definition of the utility function should explicitly incorporate these elements to more accurately represent the decision-making process (Canales et al., 2024).

This study examines winegrowers' willingness to adopt sustainable on-field practices within the framework of eco-schemes. Participation in these programs is voluntary and influenced by various factors, including conservation intensity, incentive structures, monitoring requirements, business benefits, and adoption risks. Through a discrete choice experiment, we estimate winegrowers' willingness to accept (WTA) monetary incentives for adopting specific practices, such as spontaneous and pollinator-friendly inter-row cover cropping, minimal soil tillage, and pesticide- or herbicide-free practices. Our study contributes to this literature by explicitly incorporating asset integration into a non-linear expected utility framework, thus accounting for the interaction between farm-level wealth and the stochastic outcomes of practice adoption. Asset valuation is based on farm-level data, with wealth measured from self-reports of assets and liabilities collected around the experiment date. Although less precise for tax purposes than administrative records, these self-reports are equally relevant for our purposes, as choice behavior may depend as much on perceived as on actual net wealth. We complement this with measures of background income. Within our framework, the argument of the non-linear utility function is given by the sum of background assets (or income) and the stochastic net returns from adoption. This formulation allows us to capture how winegrowers integrate—or fail to integrate—their financial baseline when evaluating risky prospects. Our findings show that participants integrate only a small, often statistically not significant, fraction of their wealth into risky decision-making.

By combining risk preference elicitation with explicit asset and income integration in

the utility specification, we provide a more realistic representation of decision-making in sustainable agriculture. The results offer actionable insights for designing incentive programs that consider both the perceived and actual economic contexts in which farmers operate.

3.2 Background and Theory

3.2.1 Asset Integration and the Argument of the Utility Function

Understanding how farmers evaluate risky prospects is central to the analysis of agricultural decision-making under uncertainty. In viticulture, as in other agricultural sectors, the adoption of sustainable practices often entails uncertain changes in production costs, yields, and revenues (Canales et al., 2024). These uncertainties shape the distribution of net returns and influence the level of incentives required to encourage participation in sustainability programs. To capture these behaviors accurately, it is essential to examine not only farmers' risk preferences but also how they integrate existing assets and wealth with the outcomes of risky choices.

A fundamental assumption in EUT is that individuals maximize expected utility defined over *terminal wealth*. However, the axioms of EUT do not specify that terminal wealth must be the argument of the utility function (Von Neumann and Morgenstern, 1947). Alternative conceptualizations have used income (Vickrey, 1945), vectors of contingent commodities (Arrow, 1964; Debreu, 1976), or mixed specification of wealth and income (Luce and Raiffa, 2012). The choice of argument is not trivial: it carries strong implications for the inference of risk preferences.

In agricultural decision-making, the assumption of full integration of background wealth with small-stakes outcomes could be particularly problematic. When terminal wealth is used as the argument and farmers reject small-stakes gambles, the implied curvature of the utility function yields implausibly high levels of risk aversion for large-stakes decisions.

This phenomenon—known as the *concavity calibration critique*, formalized by Rabin (2000). Small-stakes risk aversion, when interpreted through a terminal-wealth utility function, leads to predictions that farmers would reject highly profitable but risky opportunities, a behavior inconsistent with actual agricultural investment patterns.

A parallel critique applies when utility is defined solely over the stake or income without wealth integration. In such cases, rejecting small-stakes gambles may imply unreasonably low or high risk aversion for larger stakes, giving rise to *payoff calibration critiques* (Cox and Sadiraj, 2006; Rieger and Wang, 2006). Both critiques underscore the need to move beyond extreme assumptions of either full integration (terminal wealth) or no integration (income-only).

Empirical evidence supports this intermediate view. Using experimental lotteries linked to administrative wealth records, Andersen et al. (2018) show that individuals typically integrate only a small fraction of their wealth with experimental payoffs. This *partial integration* resolves the paradoxes associated with terminal wealth models and aligns expected utility calculations with realistic behavioral patterns. For farmers, whose wealth is often tied up in land, equipment, and long-term investments, partial integration is particularly plausible. The marginal change in terminal wealth from a program-induced shift in net returns may be small relative to total assets, but still substantial enough to influence the evaluation of uncertainty.

3.2.2 Stochastic Net Returns and the Role of Risk Preferences

In the context of sustainable agriculture, adoption decisions often involve uncertain net returns driven by weather risk, ecological performance, and fluctuating market conditions (Chavas and Nauges, 2020). Farmers' evaluation of these stochastic outcomes is highly sensitive to their underlying risk preferences. Although a large share of the literature measures these preferences through experimental tasks or surveys (Iyer et al., 2020), recent evidence indicates that elicited risk attitudes may be context-dependent and shaped by cognitive processes

activated during elicitation (Finger et al., 2023). This underscores the value of embedding uncertainty directly into stated-choice experiments, wherein stochastic attributes reflect real-world adoption conditions (Canales et al., 2024).

Standard EUT assumes linear treatment of probabilities, meaning that farmers attend to objective probabilities as presented. However, decades of behavioural evidence demonstrate that individuals regularly transform probabilities in nonlinear ways. The Allais paradox (Allais, 1953) revealed systematic violations of EUT through patterns of overweighting of small probabilities and underweighting of moderate and high probabilities. Such distortions motivate the use of nonlinear probability weighting functions, such as those proposed by Prelec (1998), within agricultural decision models.

3.2.3 Probability Weighting and Calibration Critiques

While nonlinear probability weighting captures realistic features of human judgment, it also introduces its own calibration challenges. Within models that incorporate nonlinear weighting—such as Rank-Dependent Utility (RDU), Cumulative Prospect Theory (CPT), or weighted utility forms—small-stakes choices can again impose implausible implications for large-stakes behavior unless the probability transformation is carefully calibrated (Hansson, 1988; Safra and Segal, 2008). This critique, known as the *probability calibration critique*, demonstrates that assumptions about subjective probability transformation can drastically influence estimated risk preferences.

Cox et al. (2013) and Sadiraj (2014) formalize these concerns, illustrating that models combining concave utility and inverse S-shaped weighting can produce behaviorally unrealistic predictions if not appropriately parameterized. Given that winegrowers confront both low-probability catastrophic events and moderate-probability yield fluctuations, addressing probability calibration is essential for producing credible estimates of risk preferences in agricultural contexts.

3.3 Method and Data

3.3.1 Survey Implementation and Data

Between August and December 2024 questionnaire data were collected with a stated preference survey administered to companies managing vineyards and wineries across Italy. A total of 3,287 companies were contacted, of which 432 expressed an interest in participating. Out of these, 290 completed correctly the survey, resulting in a final response rate of 8.8%.

The summary statistics of the farms analyzed in this study are presented in Table 12.

The average farm size in our sample is 126.84 hectares, significantly above the average farm size in the Italian wine sector (ISMEA-Istituto di Servizi per il Mercato Agricolo Alimentare, 2024). This because our study focuses on medium and large-scale farms, including entities such as cooperative wineries, which manage areas exceeding 1,000 ha of vineyards. More than 46% of sampled companies produce between 50,000 and 100,000 bottles per year or between 100,000 and 300,000, with an average of 43.69% of production being exported. This aligns with the national production structure, which allocates 44% of production to export markets (ISMEA-Istituto di Servizi per il Mercato Agricolo Alimentare, 2024). The gross sales value for the winegrowers in our sample is distributed as follows:

a) 26.21% of farms fall within the €1 to €5 million sales category,

b) 19.66% within the €500,000 to €1 million category, and

c) 17.59% within the €250,000 to €500,000 category.

By contrast, farms with sales below €100,000, which account for approximately 20% of Italian wine-producing farms, are relatively under-represented, with only 8.62% of the farms in our sample.

The variables relating to wealth (W) included in our experiment were defined as follows:

Table 12: Wineries Characteristics

Variable	**N**	**Mean**	**Std. Dev.**
Age	290	46.37	12.59
Male	290	76.90%	–
Education			
High school (or lower)	290	39.31%	–
Degree	290	50.69%	–
Postgraduate degree	290	10.00%	–
Role			
External consultant	290	3.45%	–
Employee	290	42.76%	–
Owner	290	53.79%	–
Work experience			
0-3 years	290	3.79%	–
3-8 years	290	15.17%	–
8-15 years	290	16.90%	–
More than 15 years	290	64.14%	–
Vineyard area	290	126.84	488.86
Production 2023 (bottles)			
less than 20,000	290	5.86%	–
20,000 - 50,000	290	15.52%	–
50,000 - 100,000	290	23.10%	–
100,000 - 300,000	290	23.79%	–
300,000 - 500,000	290	7.59%	–
500,000 - 1,000,000	290	9.66%	–
1,000,000 - 5,000,000	290	11.03%	–
more than 5,000,000	290	3.45%	–
Share of Production Exported	290	43.69	25.28
Gross sales value 2023 (Euro)			
less than 40,000	290	3.45%	–
40,000 - 100,000	290	5.17%	–
100,000 - 250,000	290	11.38%	–
250,000 - 500,000	290	17.59%	–
500,000 - 1,000,000	290	19.66%	–
1,000,000 - 5,000,000	290	26.21%	–
more than 5,000,000	290	16.55%	–
Employees			
0-2	290	28.62%	–
2-5	290	27.59%	–
5-10	290	22.07%	–
more than 10	290	21.72%	–
Organic farming	290	45.17%	–

- **W_{rev}:** company net revenue from the sale of the final product, expressed as the median value of the declared income class and adjusted for taxes

- **W_{vin}:** area under vine in hectares and corresponding average real estate market value for the specific region

Data are based on self-reported information collected during the survey and integrated with official data (Osservatorio del Mercato Immobiliare, 2019). Our dataset comprises economic, production, and personal information pertaining to both the firm and the respondent representing it in the study. Personal information includes age, gender, educational attainment, role within the company, and years of experience in the wine sector.

3.3.2 Choice Experiment Design

The characteristics of the contract proposed in the discrete experiment design were selected to mimic the eco-schemes 2 and 5 proposed by Italy (Italy's CAP Strategic Plan, 2022) within the existing framework of CAP 2023-2027. The conservation contract attributes and associated attribute levels in our choice experiment are presented in Table 13.

1. *Sustainable Conservation Practices*: winegrowers were required to adopt a package of up to four different conservation practices (inter-row spontaneous and pollinator-friendly cover crops practices were designated as mutually exclusive). The practices for each contract were presented as a bundled set of obligations, mimicking the structure of eco-schemes. For the experimental design, conservation practices were treated as dichotomous attributes.

2. *Payment*: annual incentive payment per hectare received for adopting and implementing the specified package of conservation practices.

Table 13: Characteristics of the contract for adopting sustainable practices

Attribute	**Levels**
Inter-row spontaneous cover crops	1 if included, 0 otherwise
Inter-row pollinator-friendly cover crops	1 if included, 0 otherwise
Minimum soil tillage	1 if included, 0 otherwise
No-herbicides	1 if included, 0 otherwise
No-pesticides	1 if included, 0 otherwise
Payment (Euro/ha year)	150, 250, 500, 650, 800
Incentives mechanism	Cap-and-trade biodiversity credits=1; Public subsidies=0
Benefits	Brand=1; Vineyard health=0
Monitoring	Private=1; Public=0
Risk: impact on net returns (2 under levels)	
Average change on net returns over 5 years[a]	-5%, 0%, +5%
	-10%, 0%, +10%
	-15%, 0%, +15%
Probability of changes in net returns[b]	30% loss, 40% no change, 30% gain
	10% loss, 80% no change, 10% gain
	5% loss, 60% no change, 35% gain
	35% loss, 60% no change, 5% gain

Note: [a] Each row in the Average change on net returns over 5 years under level represents a net return distribution in which is possible to have losses (negative values), no change in net returns (0) or gains (positive values).
[b] Each row in the Probability of changes in net returns under level represents the probability of loss, no change, and gain occurring for the associated net return distribution.

3. *Incentives mechanism*: we evaluated two types of incentive mechanisms, a state-run program and a program involving the payment of biodiversity credits through a market-based system.

4. *Benefits*: we assessed the extent to which preferences were influenced by market-related economic factors, such as access to niche markets and brand enhancement, or by farm-related assets, such as vineyard health and productivity.

5. *Monitoring*: one of the key factors limiting adoption rates is the control and measurement of outcomes (Calliera et al., 2021). We evaluated preferences for a monitoring system managed by private entities or public institutions.

6. *Program Risk*: the implementation of the sustainable practices may elevate income risk due to fluctuations in production costs and vineyard yields. The risk associated with contractual agreements was incorporated into the experimental design by presenting a probability distribution of potential changes in average net farm income over five years. Respondents were provided with a discrete symmetric probability distribution outlining potential loss, no change, or a gain in net returns under the adoption of practices (e.g. 5% loss, no change, or a 5% gain). The probability of each outcome was modeled using four distinct probability distributions linked to potential changes in net returns. Two of these distributions were symmetric, with equal probabilities of losses and gains.

   (a) The first distribution (30% probability of loss, 40% probability of no change, 30% probability of gain) represented a scenario with *high uncertainty*, where the likelihood of all three outcomes was *nearly equal*.

   (b) The second distribution (10% probability of loss, 80% probability of no change, 10% probability of gain) depicted a situation where net returns were highly likely to remain unchanged, with *low and equal probabilities of losses or gains*.

(c) The third distribution (5% probability of loss, 60% probability of no change, 35% probability of gain) was *skewed toward gains*, while the fourth distribution (35% probability of loss, 60% probability of no change, 5% probability of gain) was *skewed toward losses*.

In designing the discrete choice experiment, we initially developed an optimal orthogonal-in-the-differences design. This was used in a pilot study involving a sample of 40 winegrowers, following the design principles outlined by (Street et al., 2001, 2005). Subsequently, we used the parameters obtained from the pilot study to obtain a Bayesian average D-error minimizing efficient design. Design simulations were run with 500 Halton draws producing an average D-error of 0.143, on a , design with 192 choice tasks (Ferrini and Scarpa, 2007a; Scarpa and Rose, 2008; Bliemer and Rose, 2010, 2011; Rose and Bliemer, 2013a). The 192 choice sets were orthogonally divided into 24 blocks, each consisting of 8 tasks.

Every winegrower evaluated 8 contract scenarios. Each scenario included one incentive-based program and a status quo option, giving rise to a binary response to ensure incentive compatibility (Carson and Groves, 2007; Collins and Vossler, 2009; Czajkowski et al., 2017a; Canessa et al., 2023). The description of the contract attributes presented to winegrowers was delivered in multiple formats: it was provided in written form before the choice experiment, explained orally during the CATI survey's presentation phase, and integrated into the online choice cards as informational text links accessible via an "i" icon for each attribute level.

3.3.3 Choices Under Uncertainty and Asset Integration

We assume that wine producers deciding whether to adopt a voluntary incentive-based program for sustainable practices behave as expected-utility maximizers whose choices reflect underlying risk preferences. Net returns are inherently stochastic because they depend on uncertain market conditions, weather variability, and agronomic factors.

Let π_{nq} denote the expected net return of farmer n under the status quo, and let π_{nj} denote

the expected net return, excluding incentive payments, under program j. The associated variances, $\sigma^2_{\pi q}$ and $\sigma^2_{\pi j}$, capture the uncertainty surrounding these income streams.

We define the indirect utility of alternative j for farmer n as a function of both program attributes X_j and stochastic net returns:

$$V_{nj} = [X_j,\ F(\pi_{nj}(\sigma^2_{\pi j}))]. \tag{9}$$

Stochastic Net Returns and Probability Weighting. Following Prospect Theory (Tversky and Kahneman, 1992) and its development in stated-choice modelling (Hensher et al., 2015), we recognize that individuals do not evaluate objective probabilities linearly. Instead, they transform them using nonlinear probability weighting functions that overweight(underweight) low probabilities and underweight(overweight) high probabilities. This feature captures behavioral regularities suggested in the Allais paradox (Allais, 1953).

We adopt the probability-weighting functions proposed by Prelec (1998), which generalize earlier one-parameter (Tversky and Kahneman, 1992) and two-parameter (Goldstein and Einhorn, 1987) forms while offering superior behavioral flexibility. Let p_0 denote the probability associated with a given stochastic outcome in net returns. The one-parameter Prelec weighting function is:

$$w(p_0) = \exp\left[-(-\ln p_0)^{\gamma}\right], \tag{10}$$

where $\gamma > 0$ governs curvature. Values of $0 < \gamma < 1$ generate inverse S-shaped weighting with overweighting of low probabilities and underweighting of high probabilities.

The two-parameter Prelec function allows probability elevation to vary independently from curvature:

$$w(p_0) = \exp\left[-\tau(-\ln p_0)^{\gamma}\right], \tag{11}$$

where $\gamma > 0$ determines curvature and $\tau > 0$ determines elevation (Gonzalez and Wu, 1999; Hensher et al., 2011). When $\gamma = \tau = 1$, $w(p_0) = p_0$, recovering the linear weighting of expected utility theory (EUT). As γ decreases below one, diminishing sensitivity near the boundaries $p_0 \to 0$ and $p_0 \to 1$ intensifies.

Risk Preferences and Asset Integration. To model risk attitudes, we use a constant relative risk aversion (CRRA) specification (Blanchard, 1989), where utility over net returns x_m is:

$$v_n = \frac{x_m^{1-\alpha_n}}{1-\alpha_n}, \tag{12}$$

and α_n is the farmer-specific coefficient of risk aversion (Pratt, 1964). The concave form reflects diminishing marginal utility under risk aversion.

Building on Andersen et al. (2018), we incorporate *asset integration* to allow decision-makers to integrate background wealth with outcomes from the experimental or policy scenario. This yields a generalized utility function:

$$v_n = \frac{(\omega_n W_n + x_m)^{1-\alpha_n}}{1-\alpha_n}, \tag{13}$$

where W_n represents background wealth (coded in €1,000s) and $\omega_n \in [0, 1]$ is an estimable integration parameter. If $\omega_n = 0$, respondents evaluate outcomes in isolation (narrow framing). If $\omega_n = 1$, they fully integrate background wealth. Intermediate values indicate partial integration, consistent with empirical findings in experimental economics.

Extended Expected Utility Term. Combining stochastic net returns, nonlinear probability weighting, and asset integration yields an attribute-specific extended expected utility term for farmer n:

$$EEUT_n = \frac{\sum_m w_n(p_m)\,(\omega_n W_n + \pi_m)^{1-\alpha_n}}{1-\alpha_n}, \tag{14}$$

where p_m denotes the probability of outcome m, and $w_n(p_m)$ is the probability weighting function defined in Eqs. (10)–(11). This formulation simultaneously captures (i) the stochastic nature of agricultural returns, (ii) nonlinear probability perception, (iii) individual risk preferences, and (iv) the degree of wealth integration. It is consistent with attribute-specific extended expected utility theory (EEUT) as applied in behavioural choice modelling (Hensher et al., 2011).

3.3.4 Empirical Approach

The empirical application of our model focuses on estimating the determinants of the adoption of sustainable practices in incentive-based programs, the risk associated with expected net returns, and the assessment of how much of the wealth (also in terms of natural capital) is integrated into an assessment that assumes a condition of risk and uncertainty. The EEUT functional form in Eq. 15 is embedded in the utility function in Eq. 16. This, assuming random utility maximization, introduces nonlinearity in a value specification of net returns conditional on the assumed probability weighting $w(p)$ (Hensher et al., 2011). The specific equations are as follows:

$$\begin{aligned} EEUT_{njt} =& w_n(p^1_{njt})\frac{(\omega_n W_n + \pi_0 - \Delta\pi_{loss})^{1-\alpha_n}}{(1-\alpha_n)} + \\ & w_n(p^2_{njt})\frac{(\omega_n W_n + \pi_0)^{1-\alpha_n}}{(1-\alpha_n)} + \\ & w_n(p^3_{njt})\frac{(\omega_n W_n + \pi_0 + \Delta\pi_{gain})^{1-\alpha_n}}{(1-\alpha_n)} \end{aligned} \tag{15}$$

$$\begin{aligned} U_{njt} =& ASC_{program} + \beta^{€} Pay_{njt} + \sum_k \beta^k X_{ijtk} + \beta^{EUT}_n EEUT_{njt} + \\ & \sum_p \beta^p_n Practice_{njtp} + \varepsilon_{njt}, \end{aligned} \tag{16}$$

where $ASC_{program}$ is an alternative specific constant that captures the utility of entering the program, $EEUT$ is the attribute-specific extended expected utility, β_{EUT} is the expected

marginal utility from the expected net returns under risk, considering the winemaker's risk preferences and subjective assessment of utility, and $w(p)$ is a nonlinear probability weighting function given by equations 10 or 11.

The term in equation 15 is the individual probability-weighted average utility, assuming a general power specification, of three potential outcomes in terms of net returns expressed as percentages, where π_0 represents the net returns in the status quo (i.e., $\pi_0 = 100\%$ of the status quo net returns), $\Delta\pi_{loss}$ represents a decrease in percent of net returns, and $\Delta\pi_{gain}$ is the potential increase in percent net returns. In this model, α_n is the risk aversion coefficient of the single winegrower n, ω_n is the extent to which farm assets are integrated in the valuation.

We assume the presence of unobserved heterogeneity in respondents' preferences regarding risk-taking behavior and the adoption of sustainable practices. To account for this aspect, we posit that α_n is a random parameter such that $\alpha_n = \alpha_0 + \sigma_\alpha z_n$, where $z_n \sim N(0,1)$. Additionally, subjective probability assessments and asset integration by individuals are likely to vary randomly within the population. Consequently, we assume that the parameters γ, τ and ω are also random, such that $\gamma_n = \gamma_0 + \sigma_\gamma z_n$ and $\tau_n = \tau_0 + \sigma_\tau z_n$ and $\omega_n = \omega_0 + \sigma_\omega z_n$where all $z_n \sim N(0,1)$.

$Practice$ is a dummy that equals one if the practice $p = \{SPO, BEE, TIL, HER, PES\}$ is required under the sustainable program. Farmers likely exhibit unobserved heterogeneity due to unobserved factors that influence their adoption decisions regarding different practices. In this context, we assume that the respondent-specific parameter for each sustainable practice p is given by $\beta_{np} = \beta_{p0} + \sigma_p z_n$ where $z_n \sim N(0,1)$. Given our sample of surveyed winegrowers, several farmers had already adopted some conservation practices.

3.4 Results

The estimation results reported in Table 14 provide preliminary evidence on farmers' decision-making under risk in the context of adopting sustainable practices within the EU's Eco-

schemes framework, with particular attention to the integration of pre-existing assets, the elicitation of risk preferences, and the weighting of probabilities.

Across all probability–weighting specifications and for both wealth indicators (W_{rev} and W_{vin}), the estimated coefficient of the asset–integration parameter (ω_0) remains extremely small in magnitude (between 0.000 and 0.002) and never statistically significant. Quantitatively, these estimates imply that farmers integrate less than €2 for every €1,000 of wealth into the evaluation of risky prospects, and in several specifications the implied integration is below €0.10 per €1,000. This pattern parallels empirical findings showing that background wealth plays a negligible role in risky decision making (Andersen et al., 2018; Charness et al., 2020; Cohen and Einav, 2007). The results therefore support the *narrow-framing* hypothesis, consistent with expected-utility models in which asset integration is empirically close to zero (Cox and Sadiraj, 2006; Rabin, 2000).

Although the mean parameter ω_0 is not significant in any model, the random–coefficient estimates (σ_ω) show statistical significance in three of the four specifications (e.g., $\sigma_\omega = 0.002$, $p < 0.01$, in the two–parameter Prelec model with W_{rev}). Yet, even when significant, the associated magnitudes are economically trivial, reinforcing the conclusion that heterogeneity in wealth integration is minimal. Similar evidence of limited explanatory power of wealth-related heterogeneity has been documented in studies of subjective data and risk modelling (Drerup et al., 2017). Overall, the behavioral patterns observed here indicate that farmers ignore background assets when evaluating risky conservation options.

The preference parameters behave consistently with theoretical expectations. The curvature parameter α_0 is positive and highly significant across all specifications (0.39–0.47 for W_{rev} and 0.45–0.46 for W_{vin}), indicating concave utility and risk–averse behavior. Modest but significant heterogeneity in this parameter ($\sigma_\alpha = 0.042$–0.051) suggests limited variation in baseline risk preferences, consistent with canonical experimental results (Holt and Laury, 2002).

Table 14: Random Parameters Logit Results for Different Wealth Indicators

Variables	**Prelec single parameter** $w_n(p)$ **Wrev** Parameter (St. Err.)	**Prelec two parameters** $w_n(p)$ **Wrev** Parameter (St. Err.)	**Prelec single parameter** $w_n(p)$ **Wvin** Parameter (St. Err.)	**Prelec two parameters** $w_n(p)$ **Wvin** Parameter (St. Err.)
Random Parameters				
α_0	0.390*** (0.015)	0.470*** (0.058)	0.453** (0.181)	0.461*** (0.160)
σ_α	0.051*** (0.005)	0.042*** (0.007)	0.050*** (0.014)	0.044*** (0.009)
γ_0	0.753*** (0.126)	0.974*** (0.053)	0.970*** (0.060)	0.975*** (0.061)
σ_γ	−0.425*** (0.083)	0.068 (0.047)	0.053 (0.081)	0.070 (0.076)
τ_0		0.996*** (0.013)		0.996*** (0.031)
σ_τ		0.042*** (0.009)		0.035 (0.041)
ω_0	0.002 (0.002)	0.001 (0.001)	0.000 (0.000)	0.000 (0.000)
σ_ω	0.001 (0.001)	0.002*** (0.001)	0.000** (0.000)	0.000** (0.000)
μ_{SPO}	−0.095 (0.222)	−0.179 (0.226)	−0.050 (0.103)	−0.128 (0.316)
σ_{SPO}	1.328*** (0.293)	1.123*** (0.387)	0.873** (0.442)	1.058** (0.509)
μ_{BEE}	−0.154 (0.223)	−0.202 (0.213)	−0.185 (0.277)	−0.194 (0.243)
σ_{BEE}	1.023* (0.535)	1.475*** (0.283)	1.278*** (0.339)	1.429*** (0.337)
μ_{TIL}	−1.564*** (0.236)	−1.457*** (0.219)	−1.414*** (0.233)	−1.407*** (0.237)
σ_{TIL}	1.307*** (0.254)	1.474*** (0.210)	1.328*** (0.311)	1.336*** (0.336)
μ_{HER}	−0.451* (0.243)	−0.301 (0.213)	−0.306 (0.203)	−0.280 (0.211)
σ_{HER}	1.447** (0.584)	1.114*** (0.394)	0.847 (0.640)	0.975** (0.423)
μ_{PES}	−0.451** (0.199)	−0.505** (0.199)	−0.480*** (0.177)	−0.478** (0.232)
σ_{PES}	−1.010*** (0.202)	1.249*** (0.358)	0.588 (0.579)	1.105 (1.253)
Non-random Parameters				
ASC	−22.301*** (0.166)	−26.357*** (1.304)	−23.016** (10.539)	−25.383*** (3.686)
Payment	2.870*** (0.443)	2.878*** (0.448)	2.743*** (0.445)	2.813*** (0.433)
Mechanism[a]	0.205 (0.159)	0.347** (0.164)	0.260 (0.169)	0.290 (0.183)
Contract[b]	0.250 (0.166)	0.299* (0.170)	0.273* (0.159)	0.266 (0.172)
Benefit[c]	−0.059 (0.155)	−0.040 (0.156)	0.016 (0.018)	−0.026 (0.188)
β_{EUT}	0.752*** (0.026)	1.148*** (0.125)	0.960 (0.930)	1.090*** (0.338)
Log likelihood	-1118.21	-1117.89	-1118.57	-1117.94
AIC	2277.08	2286.97	2292.01	2293.68
N. observations	2320	2320	2320	2320

Note: Sustainable practices are spontaneous inter-row cover crops (SPO), pollinator-friendly inter-row cover crops (BEE), minimal soil tillage (TIL), herbicide-free practices (HER), and pesticide-free practices during flowering (PES).

[a]The incentive mechanism is a biodiversity credit payment through a cap-and-trade system, where a state-led program is the baseline.

[b]The contract type refers to a continuous agreement, where a fixed-term agreement is the baseline.

[c]The benefit is an improvement of the brand, where the improvement of the vineyard's health is the baseline.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

The probability–weighting parameter γ_0 is also positive and strongly significant (0.753–0.975), indicating systematic but moderate deviations from linear probability perception. Under the two–parameter Prelec model, $\gamma_0 \approx 0.97$ indicates nearly linear weighting, whereas under the single–parameter specification $\gamma_0 = 0.753$ (for W_{rev}) implies a more pronounced inverse–S distortion. Heterogeneity patterns are mixed: σ_γ is significant only in the single–parameter W_{rev} model. These findings are consistent with evidence that higher-order risk attitudes and probability distortions vary across individuals but remain moderate in magnitude (Noussair et al., 2014).

For the two–parameter Prelec model, the additional curvature parameter τ_0 is precisely estimated ($\tau_0 \approx 1.00$), with modest heterogeneity (σ_τ significant for W_{rev} only). This suggests greater variation in probability sensitivity when wealth is proxied by revenues rather than vineyard value.

The random parameters associated with sustainable agricultural practices reveal substantial heterogeneity. Minimal soil tillage (TIL) displays large and significant standard deviations ($\sigma_{TIL} = 1.30$–1.47, $p < 0.01$), reflecting wide divergence in preferences. Pollinator–friendly cover crops (BEE) and herbicide–free practices (HER) also exhibit strong heterogeneity across specifications. For pesticide–free practices during flowering (PES), the sign and magnitude of σ_{PES} vary considerably across models, indicating sensitivity to the assumed probability–weighting structure.

Among the non–random parameters, the payment coefficient is consistently positive and highly significant (2.74–2.88), confirming that higher compensation increases adoption likelihood. The biodiversity–credit mechanism has a modest but positive effect, significant in the two–parameter Prelec specifications (0.29–0.35), suggesting that market-based incentives are perceived more favourably than traditional state-led schemes.

Finally, the expected–utility term β_{EUT} is positive and significant in all well–identified models (e.g., 0.752^{***} in the Prelec–1 W_{rev} model and 1.148^{***} in the corresponding two–parameter

model). These values indicate that once subjective probability weighting is accounted for, farmers' choices closely approximate expected–utility predictions, consistent with structural estimations of risky choice in applied economic contexts (Canales et al., 2024; Hensher et al., 2015).

3.5 Discussion and Conclusions

The integration of background wealth into decision models provides a theoretically grounded response to calibration critiques in risk–preference estimation. Partial integration of assets smooths utility curvature and reduces the role of probability weighting in explaining risky behavior. Prior work has shown that integrating even part of background wealth can substantially alter predicted choices under risk (Andersen et al., 2018; Gu et al., 2025). However, this study finds no evidence in real-world, large-scale experiments that farmers take their existing wealth into account when assessing conservation risks.

This result has significant implications for the modeling of sustainability adoption in European viticulture. Participation in CAP eco–schemes involves adjustments with both short-term financial costs and long-term implications for resilience and environmental performance. A modeling framework that accounts for asset integration would typically allow researchers to capture how wealth shapes farmers' responses to uncertain economic outcomes. Yet, the empirical evidence here shows that asset positions do not influence experimental decisions, indicating that farmers evaluate conservation incentives through a narrow reference frame that excludes broader financial considerations.

From a policy perspective, this is a critical finding. The absence of asset integration suggests that farmers perceive the environmental objectives of Eco–schemes as largely disconnected from their long-term wealth or farm viability. In other words, the incentives embedded in CAP programs may not be sufficiently salient or credible to alter farmers' perceptions of economic risk. This echoes concerns in the literature that adoption of sustainable

practices depends heavily on perceived relevance, trust in policy stability, and alignment with farm-level goals—factors not captured merely through financial compensation.

The substantial heterogeneity observed in preferences for specific sustainable practices further suggests that a one-size-fits-all incentive structure is unlikely to yield widespread participation. Policies promoting minimal soil tillage, pollinator habitats, or pesticide reduction may require differentiated payment levels or more targeted communication strategies to align with farmers' perceptions of risk and agronomic suitability. The positive response to the biodiversity–credit mechanism indicates potential for market-based instruments, complementing state-led subsidies by offering more flexible and performance-oriented incentives.

These findings carry an important policy implication: Eco–schemes that rely solely on financial incentives may fail to engage farmers unless the environmental objectives and agronomic benefits are made more credible, relevant, and visible. The lack of asset integration indicates that farmers do not associate policy-induced environmental improvements with long-term economic resilience or wealth preservation, reducing the effectiveness of the current CAP incentive structure.

A more effective policy mix may therefore combine monetary incentives with advisory services, long-term guarantees, and participatory program design, helping ensure that sustainable practices are perceived not just as financially compensated actions but as integral components of farm strategy and risk management.

4 Ecosystem Services in Food Labels: the Role of Different Information Layers in Shaping Consumers Preferences

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Abstract

Information on the provision of ecosystem services has the potential to contribute to an integrative food labeling framework under the European Union's Farm to Fork Strategy. This study examines that potential by explicitly communicating ecosystem services provided by agricultural producers. The research analyzes how different label formats-ranging from generic references to ecosystem services to specific indicators-influence consumer preferences. A Discrete Choice Experiment was conducted with 552 Italian consumers of extra virgin olive oil. A Latent Class Model identified consumer heterogeneity, and to address the endogeneity of environmental attitudes in class allocation, a two-stage Control Function approach was applied. Two consumer segments emerged. The first, showed a consistently higher and statistically significant willingness to pay for sustainability attributes. Their willingness to pay increased with the level of informational detail. This group was highly engaged and responded positively to transparent and specific information. However, a negative halo effect was observed when ecosystem services labels appeared alongside organic certification, suggesting a perception of redundancy. The second segment displayed lower willingness to pay for ecosystem services labels and information layers. This group was more price-sensitive and resistant to additional information. In some cases, ecosystem services-related claims led to a decrease in willingness to pay, indicating

skepticism or confusion. From a policy perspective, the results indicate how ecosystem service labeling strategies, particularly when linked to measurable environmental outcomes, can stimulate market-based incentives, providing farmers with potential differentiating tools and consumers with a clearer view of the food industry's role as a natural resource custodian.

Keywords: Consumer behaviour; Agri-food sector; Discrete Choice Experiment; Ecosystem Services; Control Function

JEL Classifications: Q13; M12; L17

4.1 Introduction

Today's global food system has a significant impact on both the environment and climate. It accounts for approximately 29.7% of total greenhouse gas emissions (FAO, 2024) and is a major driver of biodiversity loss and ecosystem degradation (IPBES, 2024). At the same time, food systems play a central role in achieving key social goals, including reducing hunger and poverty (Searchinger et al., 2019). Due to this dual role—both contributing to and being affected by environmental and social challenges—there is a pressing need to transition toward more sustainable and resilient models (Schulze et al., 2024).

Policymakers have a wide range of interventions and tools at their disposal. From the producers' perspective, strategies to internalize the negative externalities of food production have primarily focused on conditional subsidy payments, as exemplified by the European Union's Common Agricultural Policy (CAP) (Pe'er et al., 2019). On the consumer side, policy efforts have largely aimed at influencing purchasing choices (Just and Byrne, 2019). Understanding public attitudes toward various policy options is essential for designing effective interventions (De-loyde et al., 2025; Reisch and Sunstein, 2016). Governments have

access to a wide range of tools to achieve consumer-focused food policy goals, including information campaigns, behavioral nudges, financial incentives (such as taxes or subsidies), and regulatory approaches. In general, consumers are more likely to support less intrusive measures—such as informational tools and nudges—than stricter options like taxes or bans, despite the latter often proving more effective (Ammann et al., 2025).

Among the less intrusive measures, front-of-pack (FOP) labels are increasingly used to help consumers make healthier and more environmentally responsible food choices (Hallström et al., 2015). These labels aim to bridge the information gap between producers and consumers by highlighting product characteristics that are difficult to observe, even after purchase—specifically, credence attributes such as environmental impact and sustainability performance (Lin and Nayga Jr, 2022). By enhancing awareness, reducing search costs, and encouraging more sustainable consumption, FOP labels also have the potential to incentivize environmentally responsible production (Carlsson et al., 2022). Gorton et al. (2021) examined the use of eco-labels—especially organic certifications in the EU—and found that they play a key role in transforming unobservable product attributes into actionable market signals.

However, many existing labels focus on broad standards, such as organic production, and fail to communicate specific environmental contributions—for instance, efforts by agricultural producers to conserve pollinator habitats or sequester carbon in soils, which more generally can be described as agriculture's contribution to the provision of ecosystem services (ES). These services, defined as the benefits people obtain from nature, are receiving increasing attention in both EU policy and academic research (Bouwma et al., 2018; Costanza, 2020; Nes and Ciaian, 2022). Yet despite their growing significance, ES remain absent from current food labeling and consumer communication frameworks.

The present study pursues a twofold aim through a discrete choice experiment (DCE) conducted on-field in a supermarket. First, it seeks to advance the literature on sustainable food labeling by investigating the potential of new labels that explicitly communicate the provision

of ES by agricultural producers. This addresses the broader challenge of making farm-level environmental contributions visible to consumers through market instruments. Second, the study explores whether label characteristics, specifically, whether the label presents general information on ES or focuses on a specific ES (i.e. biodiversity conservation for pollinators), and the level of information detail provided, influence consumer preferences. This component aims to identify how label design can support more sustainable choices by improving understanding and relevance for different consumer segments.

Helping consumers understand the environmental role of agriculture, particularly through the lens of ES, may encourage more sustainable consumption patterns. Labels that clearly convey these contributions could motivate consumers to reward producers for their efforts, enhancing the effectiveness of sustainability policies (Laksmawati et al., 2024). If consumers value these practices, targeted financial incentives could be more impactful, especially in encouraging change among less sustainable producers (Just and Byrne, 2019).

4.2 Literature Review

Emerging research has started to examine novel food labeling schemes that incorporate ecosystem services (ES). Schulze et al. (2024) explored how information on ES provision could inform future labeling practices in the EU's Farm to Fork Strategy, identifying three potential label types: producer-driven, consumer-oriented, and EU-wide sustainability labels, based on expert input from multiple countries. Their work highlights the importance of integrating diverse stakeholder perspectives in label design. The study by Voglhuber-Slavinsky et al. (2023) explores private valorization options for biodiversity and ES in the agri-food value chain and confirms that labeling has the potential to complement or even substitute public policy instruments by operating beyond the production stage and actively shaping consumer demand. Altmann and Berger Filho (2020) examined the potential of certification and labeling as economic instruments to promote biodiversity conservation and ES in the Pampa

Biome, using grassland beef certified under the "Alianza del Pastizal" scheme as a case study, demonstrating that such mechanisms can create market incentives through premium pricing, though their effectiveness depends on system design and consumer responsiveness.

Other studies have investigated how ES certification can influence market dynamics through direct consumer surveys. Jaung et al. (2019), through a DCE on bottled water with ES claims in Indonesia, found that certification improved brand equity but struggled to outperform established competitors, emphasizing the role of branding and market positioning. Borrello et al. (2022) demonstrated that cultural ES from traditional agricultural landscapes could be valued through labeling: consumers expressed willingness to pay (WTP) for products certified as linked to terraced olive groves, particularly when combined with organic and protected designation of origin (PDO) certifications.

Nevertheless, the literature has not yet explored the optimal communication strategy for ES labels—specifically, how consumers perceive, interpret, and value them, both in terms of visual design and informational content. Individuals differ in how they interpret and use labels: some rely on general food knowledge, while others depend on label familiarity (Sørensen et al., 2012), making effective label design a complex challenge (Boncinelli et al., 2023; Duckworth et al., 2022). Van Loo et al. (2015) outline the importance of label salience and consumer education, noting that visibility and clarity are essential to converting credence attributes into meaningful decisions. Informational framing is equally important: clear explanations and eco-metrics help reduce information asymmetries and build consumer trust (Aprile and Punzo, 2022). However, the complexity and multidimensional nature of ES increase the risk of information overload, which may impede consumers' ability to effectively process and act on label information (Grunert and Wills, 2007). This is further supported by a recent study on extra virgin olive oil (EVOO) across Italy, Greece, and Israel, which highlights that the abundance of certifications (e.g., PDO, organic, carbon footprint) can cause consumer confusion, ultimately diminishing the communicative effectiveness of labels (Paffarini et al.,

2025).

These elements are particularly relevant in the context of ES labeling, as ES are, by definition, a diverse set of benefits provided by nature. In the case of agriculture, these services can include provisioning services such as food, fiber, and biomass production; regulating services such as carbon sequestration, pollination, water purification, erosion control, and climate regulation; supporting services including soil fertility and nutrient cycling; and cultural services such as landscape aesthetics, cultural heritage, and recreational value (United Nations, 2025). Given the variety of services involved, communication through labeling can take two different approaches: a generic label that certifies the overall provision of ES, or a targeted label that highlights a specific ES delivered by the farm. For example, a farm could adopt a targeted labeling strategy to communicate its contribution to pollination services. In this case, a possible indicator could be the Net Pollination Index, which quantifies the contribution of on-farm practices such as the maintenance of wildflower strips, hedgerows, or pollinator habitats to pollinator activity and crop yield (Martínez-López et al., 2019).

Together, this body of evidence suggests that effective ES labels should balance visual clarity, meaningful content, and credible certification to foster informed choices and reward environmentally responsible production, especially considering that these new labels may appear alongside existing environmental (e.g., organic) or quality certifications (e.g., PDO) on the product.

4.3 Materials and Method

4.3.1 Data and Survey Design

Survey was conducted from May to August 2024, through a face-to-face field experiment approach at a supermarket chain store in Brescia, Italy. The focus of the survey was a DCE on EVOO for consumption at home. In Italy, EVOO is a widely consumed product and plays a

key role in the Mediterranean diet, being therefore often chosen for reasons related to health, culture, and product quality (Del Giudice et al., 2015; Perito et al., 2019).

The sample consisted of 552 people, aged eighteen years and older, regular consumers of EVOO (at least 2 times a week) and main responsible for their household's food expenditure. Subjects were recruited at the entrance of the supermarket store. We promoted a brief collaboration with a store belonging to a national supermarket chain present in Brescia, Italy, in a middle- to high-income neighborhood. In Mompiano, the median household annual income was estimated at €31,835, with residents accounting for 3.84% of total taxpayers in the municipality (Dipartimento delle Finanze, 2022).

A preliminary pilot study of 52 students was conducted to test the clarity of the experiment, the quality of the responses and to optimize the experimental design.

The questionnaire was structured into four main sections. The first investigated awareness and attitudes related to sustainability of food supply chains. The second section contained the DCE. To ensure data quality, before presenting the set of choice tasks, we asked respondents whether they had "devoted their full attention to the questions up to that point" and whether, in their honest opinion, they felt we should have used their answers for the study (Meade and Craig, 2012). We strategically placed this question immediately before more important ones, such as choice tasks (Asioli et al., 2022). Prior to the DCE tasks respondents were also instructed on how to complete the DCE and given a cheap talk script to mitigate hypothetical bias (Cummings and Taylor, 1999). The third section investigated knowledge and usage habits related to food labels and ES, with self-reported labels use questions and specific multiple-choice quizzes. The last section, with socio-demographic questions, concluded the questionnaire.

4.3.2 Experimental Design

Different labeling strategies have been investigated using DCEs, which allows the estimation of a welfare measure in terms of citizens' marginal willingness to pay (mWTP) for different labeled information options (Bazzani et al., 2025; Lusk et al., 2018; Thiene et al., 2018; Van Loo et al., 2014). Some of the most relevant studies evaluating how environmental impact information drives consumer choices have implemented this approach (Lin and Nayga Jr, 2022; Mameno et al., 2023). Hypothetical DCE was also used to elicit preferences for different qualities of EVOO (Panico et al., 2014; Scarpa and Del Giudice, 2004). DCEs allow to decompose the good into different attributes, estimating preferences for each of them and representing the decision-making mechanisms that individuals enact in a context such as the supermarket (Caputo et al., 2023; Cerroni et al., 2019; Grebitus et al., 2013; Muller et al., 2019).

The first step in designing the experiment was to define the product, which is an EVOO in a one-liter bottle. EVOO was selected as case study because in Italy EVOO production represents one of the main permanent tree productions, occupying about 8 percent of the total UAA (ISTAT, 2021). Second, areas designated for EVOO production generally represent an ecosystem with important potential for the conservation and maintenance of biodiversity (Salazar-Ordóñez et al., 2021). Moreover, in Italy, EVOO production has been abandoned in some areas in the last 5 years (Mediobanca - Area Studi, 2024), representing the potential case study of the effective capacity of a labeling strategy on the provision of ES as an incentive for a premium price to make production economically viable.

Second phase involved the selection of attributes and related levels to describe the EVOO bottle proposed in the experiment (15).

Given the intention to also investigate the effect of co-occurrence with the most common labeling types associated with EVOO, labels for organic certification and designation of origin were selected. For the former, levels indicating the presence or absence of the logo were

Table 15: Attributes and Levels Considered in the Choice Experiment

Attributes	**Levels considered**	**Logo**
Ecosystem Services	• None • ES logo	
Organic	• None • EU Organic logo	
ES Maintenance of Biodiversity	• None • Farming for Biodiversity	
	• Farming for Biodiversity + Bees	
	• Farming for Biodiversity + Bees + Net pollination index	
Designation of origin	• None • PGI	
	• PDO	
Price	• 9,1 € • 10,6 € • 12,1 € • 13,6 € • 15,1 €	

included. For the latter, levels corresponding to absence, Protected Geographical Indication (PGI), and PDO were selected.

Regarding the provision of ES two hypothetical attributes were employed. The first represents a general informational level about the provision of generic ES and was labeled "Ecosystem Services", with levels indicating presence or absence. The second specifically describes the provision of the ES related to biodiversity conservation through the preservation of pollinator species. For this specific attribute, levels of increasing informational detail were selected: an absence level, an initial informational level labeled "Farming for Biodiversity", an enhanced level "Farming for Biodiversity + Bee", which includes the image of a bee to represent the service being provided, and a further detailed level, "Farming for Biodiversity + Bee + Net Pollination Index", which introduces a value scale based on the Net Pollination Index (Martínez-López et al., 2019). The idea that communicating to consumers the efforts and services that producers can potentially offer to the community may provide producers with new opportunities for product differentiation motivated the selection of these attributes. Finally, based on data from the Italian bottled EVOO market and current literature, the price attribute for one liter bottle of EVOO was constructed with five levels (9.12€, 10.6€, 12.1€, 13.6€ and 15.1€) to provide a wide range for respondents.

In designing the DCE, we initially developed an optimal orthogonal in differences design. This design was employed in a pilot study involving a sample of 52 students, following the design principles outlined by Street et al. (2001, 2005). Subsequently, the parameter estimates obtained from the pilot study were used to generate a Bayesian D-efficient design aimed at minimizing the average D-error. Design simulations were conducted using 500 Halton draws, resulting in a design comprising 36 choice tasks (Bliemer et al., 2008; Ferrini and Scarpa, 2007b; Rose and Bliemer, 2013b; Scarpa and Rose, 2008). The 36 choice sets were orthogonally divided into four blocks, each consisting of nine tasks. This means that each respondent was randomly assigned to one block and asked to evaluate nine purchase

scenarios. Each scenario presented two product alternatives and a third opt-out alternative (no purchase).

4.3.3 Choice Tasks and Treatment Design

As an introduction to the DCE, respondents were instructed on the mechanism of the experiment. They were asked to imagine themselves in a real-life choice situation within the supermarket and that they would have to select one liter bottle of EVOO for home consumption under nine different scenarios. Respondents were asked to indicate their preferred option based on the label information provided or to opt-out if none of the alternatives were considered acceptable. To reduce potential hypothetical bias, the DCE was preceded by a brief and neutral "cheap talk" script (Cummings and Taylor, 1999).

In addition, respondents were randomly assigned to one of two treatment groups that differed in the presence of an additional informational component external to the product label. In detail, in the "Info=0" treatment, participants were presented with choice tasks preceded by a brief and generic introduction to ES. In contrast, in the "Info=1" treatment, respondents were provided with an explanation prior to the choice tasks detailing how ES are measured, and what the information on the hypothetical labels really represents. For example, the Net Pollination Index was explained, as an index that ranges from -1 to +1 and measures how well an ecosystem supports crop pollination. Habitats such as forest edges and flowering hedgerows help pollinating insects. An olive grove that preserves these habitats and reduces pesticide use will have a positive index (0 to +1). Conversely, a field that does not preserve these habitats and reduces the availability of shelter and protection for pollinator species will have a negative index (0 to -1) (Martínez-López et al., 2019). This information covered both the general informational levels of the labels and the more detailed information levels, elaborating on the methods used for measuring and representing the ES. This approach was intended to simulate a potential external informational campaign, distinct from product

labeling, as a form of nudging, assessing the effect of additional off-label information and information asymmetry gap filling on consumer preferences.

4.3.4 Econometric Approach

Latent Class Model: From DCEs data, estimates of structural discrete choice models (DCMs) can be obtained. DCMs are consistent with random utility theory (McFadden, 1974), which states that the utility that individual n gets from alternative j in the set of choices t can be decomposed into an observed, deterministic part (V_{njt}) and an unobserved, random part (ε_{njt}):

$$U_{njt} = V_{njt} + \varepsilon_{njt} = ASC_j + x'_{njt}\beta + \varepsilon_{njt} \tag{17}$$

where x'_{njt} is a vector containing attributes of the asset to be evaluated, β is the vector of corresponding parameters, ASC_j are the alternative specific constants. This structure of utility is consistent with Lancaster's (Lancaster, 1966) theory, which assumes total utility resulting from the choice of a product as a decomposition of additive utilities arising from the attributes of the product itself.

The literature on consumer behavior in relation to food labels shows that consumers have heterogeneous preferences (Lusk et al., 2003). Heterogeneity of preferences (e.g., taste variation) in sustainability claims must also be considered for correlation between utilities and between taste parameters (Van Loo et al., 2014). Heterogeneity can be assumed to be continuous or discrete, and recent literature has shown that taste variation has asymmetric and multimodal distributions (Caputo et al., 2018; Scarpa et al., 2021).

An initial approach on the continuous and discrete nature of heterogeneity was conducted using Mixed Logit models in WTP space (Scarpa and Rose, 2008; Train and Weeks, 2005). The results showed a multimodality of preferences distributed in subgroups that supports our latent class model (LCM) approach.

LCM consists of a structural equation for the choice model (Equation 17) and a class allocation function (Greene and Hensher, 2003a). In LCMs, individuals are indirectly allocated into q classes, and the researcher is unable to know which class an individual belongs to. The probability that an individual n will choose an alternative i is the logit probability conditional on membership in class q. The probability of sequence of choices of individual n is then represented as:

$$P_n(i|q) = \prod_{t=1}^{T} P_{nit}(i|q) = \prod_{t=1}^{T} \left(\frac{\exp(ASC_i + x'_{nit}\beta_q)}{\sum_{j=1}^{J} \exp(ASC_j + x'_{njt}\beta_q)} \right) \tag{18}$$

The probability Ψ_{nq} that individual n belongs to class q is modeled as a logit probability:

$$\Psi_{nq} = \frac{\exp(\gamma_{0q} + z'_n\gamma_{1q})}{\sum_{q=1}^{Q} \exp(\gamma_{0q} + z'_n\gamma_{1q})} \tag{19}$$

where z'_n are observable exogenous characteristics (e.g., sociodemographic), γ_{1q} is the corresponding parameter vector, and γ_{0q} are constant terms.

The unconditional probability that individual n will make the set of choices will be given by the sum of the conditional probabilities on the q classes (Equation 18), weighted by the probability of membership in each class (Equation 19) (Mariel et al., 2025). It is not possible to estimate the number of classes a priori, but it is necessary to orient based on informative criteria about the model fit, as well as the researcher's judgment (Scarpa and Thiene, 2005).

Endogeneity in the allocation function of an LCM and the two-step Control Function approach: A growing body of literature describes the influence of individual attitudes toward an environmental good or service on environmental valuation (Hess et al., 2013). Heterogeneity of preferences, particularly in an LCM, shows its best representation with the inclusion of such attitudes. While generally the problem related to endogeneity concerns the structural equation (Guevara, 2018), it can also occur in the allocation function of an LCM.

As described in Mariel and Arata (2022), this function can be seen as the propensity to belong to a specific class q, and can be described as:

$$F_{nq} = \gamma_{0q} + z_n'\gamma_{1q} + \gamma_{2q}s_n + \xi_{nq} \tag{20}$$

where z_n is a vector of observable exogenous characteristics (e.g., sociodemographic), s_n is a vector of individual attitudes (e.g., attitudinal scale) and γ_{0q}, γ_{1q} and γ_{2q} are the corresponding parameters.

Assuming that s_n is defined as:

$$s_n = \alpha_0 + c_n'\alpha_1 + \eta_n \tag{21}$$

where c_n is a vector of exogenous variables independent of error terms ξ_{nq} in Equation 20 and η_n, and α_0 and α_1 are unknown parameters. The vector c_n may contain all or some of the observable exogenous variables z_n in Equation 20.

Therefore, assuming the influence of individual attitudes related to the environmental good or service $(\gamma_{2q} \neq 0)$, we could have endogeneity in Equation 20 due to the omission of the relevant variable (s_n); due to the measurement error of the attitude itself (under appropriate assumptions); or in the case where the error terms ξ_{nq} in Equation 20 is correlated to the error term η_n in Equation 21. In the latter case, s_n in Equation 20 is endogenous by definition (Alcorta and Mariel, 2025).

Our case study evaluates the inclusion of an endogenous indicator (s_n) representing individuals' attitudes toward the sustainability of the agribusiness supply chain. This is the case where, as the classes defined by Equation 21 are representative of preferences for label information regarding the environmental sustainability of EVOO production, the error terms ξ_{nq} and η_n are correlated.

To address this potential endogeneity problem, we apply the two-stage Control Function

(CF) approach (Guevara and Polanco, 2016a). In the first stage, the attitudinal indicator is regressed on the exogenous variables z_n, on an instrumental variable Instr_{1n} for which typical instrument assumptions apply (Guevara, 2018), and on two additional instruments formed by seven additional statements on sustainability of agrifood supply chain collected and used to define the two main factors from an exploratory factor analysis Fact_{1n}, Fact_{2n}:

$$s_n = \alpha_0 + z_n'\alpha_1 + \alpha_2 \text{Instr}_{1n} + \alpha_3 \text{Fact}_{1n} + \alpha_4 \text{Fact}_{2n} + \eta_n \tag{22}$$

where η_n is assumed to be i.i.d. normally distributed. Equation 22 is estimated by ordinary least squares regression to obtain the residuals $\hat{\eta}_n$. The second step of the CF approach is to include $\hat{\eta}_n$ in Equation 20:

$$F_{nq}^{CF} = \gamma_{0q} + z_n'\gamma_{1q} + \gamma_{2q}s_n + \gamma_{3q}\hat{\eta}_n + \xi_{nq} \tag{23}$$

where $\hat{\eta}_n$ residuals collect the part of s_n that generates correlation with the error term in Equation 20.

The entire DCM was estimated using Equation 23 in the LCM allocation function.

To verify the necessary condition that the instruments used in Equation 22 are exogenous, the test of refutability of instrument exogeneity was used (Guevara, 2018). The test is based on the condition of overidentification and first estimates the LCM using Equation 23 in the allocation function, then recalculates the model with a modified allocation function that includes Equation 23 with all instruments except one. The test statistic is defined as:

$$S_{ref} = -2(LL^{CF} - LL^{CF_{instr}}) \sim \chi^2_{df} \tag{24}$$

where df are the degrees of freedom equal to the number of instruments minus the number of endogenous variables. The null hypothesis of the test is that the instruments are exogenous, while the alternative hypothesis is that one or both instruments are endogenous, and it is

repeated for all possible combinations of instruments.

4.3.5 Empirical Model

The structural equation for the choice model (Equation 17) is specified as:

$$U_{nit|q} = ASC_q \left[1 + 1(\text{Inf})_n\right] + \alpha p_{nit} + \tilde{\beta}_q' x_{nit} + \delta_q \left[x_{nit} \times 1(\text{Inf})_n\right] + \gamma_q \left[x_{nit}^{ES} \times \text{Organic}\right] + \vartheta_q \left[x_{nit}^{ES} \times PDO\right] + \varepsilon_{nit|q} \tag{25}$$

where ASC denotes the alternative-specific constant for the opt-out alternative, it takes the value 1 when respondents choose not to purchase any of the proposed products. The model also includes interaction effects between ASC and an external information variable, which equals 1 if the respondent received additional information processing. The variable p_{nit} is a continuous measure representing the five price levels used in the experiment. The vector x_{nit} comprises non-price attributes, including:

1. Organic production certification, treated as dummy variable (1 if the logo is present, 0 otherwise)

2. Indicator for generic ES provision, treated as dummy variable (1 if the logo is present, 0 otherwise)

3. A variable for the specific ES attribute concerning the maintenance of biodiversity preserving pollinator species, modeled as dummies across three experimental levels reflecting increasing information content (the absence of a label serves as the reference level with a value of 0)

4. The designation of origin attribute, also represented by dummy variables for each experimental level and associated logo presence (PGI and PDO)

The parameter α denotes the marginal utility of income (i.e., the price coefficient). The vector $\tilde{\beta}_q$ includes coefficients for non-price attributes specific to class q, which are assumed to vary randomly and continuously among respondents in that class according to a normal distribution. The vector δ_q captures class-dependent, within-class fixed parameters reflecting the effects of information on the quality attributes represented by the treatment dummy variable Inf. The vector γ_q comprises class-specific fixed parameters describing the interaction effects between ES-related logos (x_{nit}^{ES}) and the "Organic" dummy. Similarly, ϑ_q represents the interaction effects between ES-related logos (x_{nit}^{ES}) and the PDO dummy. The parameters γ_q and ϑ_q describe the potential halo effect of well-recognized and widely adopted certifications (Organic and PDO) on the perception of ES-related information.

The class allocation function corresponding to Equation 20 is defined as:

$$F_{nq} = \gamma_{0q} + \gamma_{1q}\text{Female}_n + \gamma_{2q}\text{Age}_n + \gamma_{3q}\text{Education}_n + \gamma_{4q}\text{Income}_n + \gamma_{5q}\text{FullTime}_n + \gamma_{6q}\text{Household}_n + \gamma_{7q}\text{Children}_n + \gamma_{8q}\text{EnvironmentalDamage}_n + \xi_{nq} \tag{26}$$

where the attitudinal statement $EnvironmentalDamage$ is added to the sociodemographic variables to assess the potential role that attitudes toward the relationship between food production and the environment may have on individual class allocation. We applied the CF approach to consistently estimate the model defined above being this additional explanatory variable endogenous by definition (Mariel and Arata, 2022).

Finally, the negative ratio between the estimated average value of the coefficient associated with the quality attribute of the EVOO and the price coefficient was used to estimate the marginal WTP.

4.4 Results

4.4.1 Descriptive Analysis

Data were collected on a sample of 750 respondents from the adult population who frequented the selected supermarket in Mompiano neighborhood in the city of Brescia. Final sample consisted of 552 correct responses, representing 4968 observations (Table 16).

A total of 270 people were assigned to the Inf=0 group and 282 to the Inf=1 group. We conducted equilibrium checks to assess whether the two treatment groups differed systematically in their sociodemographic characteristics. χ^2 tests and Nonparametric Mann-Whitney U-tests were applied to test for significant differences between the distributions in the two subsamples with and without information, as well as p values for the test of no difference between the proportions was reported. Overall, the sample appears well balanced. Gender differences are not statistically significant, although the Inf=1 group includes a slightly higher proportion of female respondents (57.8%) than Inf=0 (51.1%). The age distribution is similar, with the largest shares concentrated in the 45-64 age group. There are no significant differences in education or employment status. Household income levels are also comparable, although the Inf=0 group includes a marginally higher proportion of low-income respondents ($\leq 15,000$€, p-value ≤ 0.091), which falls short of conventional levels.

Table 17 reports the relative frequency of scores given by respondents to attitudinal questions regarding concern about the sustainability of food production.

Table 16: Sociodemographic variables and balance tests

	Info=0 (N=270)	**Info=1 (N=282)**	**No diff. in proportion** *p-value*	**No diff. in distribution** *p-value*
Gender				0.107
Male[a]	48.1%	42.2%	0.187	
Female[a]	51.1%	57.8%	0.135	
Prefer not to answer[a]	0.8%	0.0%	//	
Age class				0.812
18-24[a]	12.2%	12.1%	0.953	
25-34[a]	18.5%	15.6%	0.425	
35-44[a]	10.7%	13.8%	0.330	
45-54[a]	20.0%	20.9%	0.871	
55-64[a]	27.4%	24.8%	0.553	
65+[a]	11.1%	12.8%	0.641	
Education				0.597
High School[a]	46.7%	48.2%	0.778	
Graduate[a]	42.2%	42.6%	0.937	
Post Graduate[a]	11.1%	9.2%	0.552	
Employment				0.522
Unemployed[a]	14.4%	12.1%	0.483	
Retired[a]	9.3%	12.8%	0.239	
Part-time Employed[a]	14.4%	12.1%	0.483	
Full-time Employed[a]	61.9%	63.1%	0.826	
Household Gross Income				0.281
$\leq$15,000€[a]	10.7%	6.4%	0.091*	
15,001-29,000€[a]	27.8%	29.1%	0.807	
29,001-55,000€[a]	38.9%	39.7%	0.912	
55,001-100,000€[a]	16.7%	18.4%	0.664	
$>$100,000€[a]	5.9%	6.4%	0.965	
Household Composition				
Household Size	2.211 (1.340)	2.131 (1.266)	//	0.382
Children Under 15	0.267 (0.646)	0.309 (0.705)	//	0.428
Environmental association membership[a]	15.2%	11.7%	0.282	

Note: [a]Dummy variable. For continuous variables values show means with standard deviations in parentheses.

Table 17: Attitudinal questions and relative frequency (%) (1 = only slightly concerned; 7 = extremely concerned)

	Label	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Environmental damage caused by human use of land and water in food production	env_damage	6.9%	10.0%	15.9%	11.1%	15.6%	17.6%	23.0%
The use of pesticides used in food production	pest	6.0%	9.1%	15.4%	10.0%	12.5%	17.4%	29.7%
Poor treatment of animals in food production	animals	8.9%	10.7%	15.8%	10.1%	14.3%	9.2%	31.0%
The process of deforestation related to food production	deforestation	4.7%	6.5%	16.3%	7.6%	13.4%	19.0%	32.4%
Using too much of the world's natural resources for food production	resources	6.3%	8.5%	15.2%	9.8%	13.2%	19.0%	27.9%
The amount of non-recyclable packaging	packages	4.5%	6.9%	15.4%	10.3%	12.5%	19.9%	30.4%
The amount of CO_2 emissions during the transportation of food products	transport	7.1%	9.2%	15.2%	11.1%	18.1%	18.7%	20.7%
The amount of energy used when cooking food products	energy	16.1%	14.5%	13.9%	15.0%	17.6%	13.6%	9.2%

The respondents were asked to rate their level of concern for various issues on a 7-point Likert scale, where 1 indicates very low concern and 7 indicates very high concern. The results reveal distinct patterns in public perception across different environmental dimensions. Overall, respondents express relatively high levels of concern for several issues. The highest levels of concern are observed for deforestation (32.4% selecting 7), poor animal treatment (31.0%), and non-recyclable packaging (30.4%). These issues are also characterized by low percentages at the lower end of the scale (4.5–8.9% selecting 1), suggesting broad consensus around their perceived severity. Similarly, pesticide use (29.7% scoring 7) and excessive use of natural resources (27.9%) are considered pressing problems by a substantial share of respondents. In contrast, concern about energy consumption during cooking shows a markedly different pattern. This is the only item for which the most frequent response is at the lower end of the scale (16.1% selecting 1, compared to only 9.2% selecting 7), indicating that respondents perceive this issue as less environmentally relevant. CO_2 emissions from food transport also rank lower in relative concern, with 20.7% selecting 7, and more evenly distributed responses across the scale. Responses regarding environmental damage from land and water use and resource overuse are relatively moderate, with around one-quarter of respondents selecting the highest concern level (23.0% and 27.9%, respectively), and notable proportions scoring in the mid-range (categories 4 and 5).

Table 18 reports respondents' levels of both prior and objective knowledge regarding four food-related label, Organic, Eco-label, PDO, and Carbon Footprint, as well as their knowledge of ES. The table displays mean values across the two treatment groups (Info=0 and Info=1), with minimal differences observed between the groups.

Overall, self-reported prior knowledge ("Have you ever seen this label?") is highest for the Organic label, with 78.1% of respondents in the Info=0 group and 75.9% in the Info=1 group reporting recognition. PDO follows, with roughly 64% of respondents indicating familiarity. In contrast, the Eco-label and Carbon Footprint label show considerably lower recognition

Table 18: Prior and objective knowledge regarding four food-related labels and ES.

Variable	Mean (SD)[a]		Min.	Max.	Labels
	Info=0	Info=1			
Labels prior knowledge declaration					
Organic label prior knowledge	78.1%	75.9%	0	1	
Eco-label prior knowledge	33.3%	28.7%	0	1	
PDO label prior knowledge	64.1%	62.4%	0	1	
Carbon foot-print label prior knowledge	17.0%	16.3%	0	1	
Labels objective knowledge					
Organic label objective knowledge	42.6%	35.1%	0	1	
Eco-label objective knowledge	40.0%	41.1%	0	1	
PDO label objective knowledge	77.0%	77.0%	0	1	
Carbon foot-print label objective knowledge	60.4%	56.4%	0	1	
Labels knowledge score (0-4)	2.200 (1.091)	2.096 (1.086)	0	4	
Ecosystem Services knowledge					
ES prior knowledge declaration	37.0%	33.7%	0	1	
ES knowledge score (0-5)	4.056 (1.145)	4.018 (1.156)	0	5	

[a]For dummy variables, values represent proportions; for categorical variables, values represent means with standard deviations in parentheses.

levels, with fewer than 35% of respondents reporting prior exposure (Hartikainen et al., 2014). These results suggest that while organic and origin-related certifications are widely recognized, environmental indicators such as eco- and carbon-labels remain less familiar to the public (Gorton et al., 2021). Objective knowledge presents a different picture. While recognition of the PDO label is high, only 77% correctly identified its meaning, indicating some consistency between familiarity and understanding. In contrast, only 35.1% (Info=1) to 42.6% (Info=0) correctly answered questions about the Organic label, revealing a potential gap between perceived and actual understanding. Carbon Footprint label knowledge is moderate (around 58%) (Rondoni and Grasso, 2021), while Eco-label understanding remains low, with only 40–41% correct answers. The composite label knowledge score averages just above 2 out of 4 in both groups, suggesting moderate overall comprehension. Regarding ES, 37.0% of the Info=0 group and 33.7% of the Info=1 group reported prior knowledge. However, the objective ES knowledge scores are relatively high, averaging around 4 out of 5 in both groups, suggesting that even among those unfamiliar with the term, conceptual understanding is strong when prompted with specific content. This is also due to the basic information received from the whole sample at the beginning of the DCE. In summary, while prior exposure to food and environmental labels varies widely, objective knowledge tends to be lower, particularly for eco- and organic labels, highlighting potential gaps in consumer understanding.

4.4.2 Estimation Results

This section reports the estimates of an LCM incorporating the potentially endogenous variable $EnvironmentalDamage$ within the allocation function. To address endogeneity, suitable instruments were required for the auxiliary equation specified in Equation 22. These instruments must be correlated with the endogenous variable but uncorrelated with the error term in the allocation function. Based on this theoretical framework, the primary instrument selected is a dummy variable indicating whether the respondent is a member of an environmental

association. To strengthen the identification strategy, two additional instruments, $Fact_1$ and $Fact_2$, were derived from an exploratory factor analysis conducted on the remaining seven attitudinal statements. The key results of this analysis are presented in Table 19.

Table 19: Exploratory factor analysis

	Eigenvalues and variability				**Factor loadings**	
Factor	**Eigenvalue**	**Variance**	**Cumulative**	**Item**	**Factor1**	**Factor2**
Factor1	5.116	88.1%	88.1%	pest	0.835	0.229
Factor2	0.343	5.9%	94.0%	animals	0.813	0.320
Factor3	0.209	3.6%	97.6%	deforestation	0.910	0.123
Factor4	0.109	1.9%	99.5%	resources	0.907	0.036
Factor5	0.025	0.4%	100.0%	packages	0.829	-0.257
Factor6	0.003	0.1%	100.0%	transport	0.891	-0.267
Factor7	0.000	0.0%	100.0%	energy	0.792	-0.184

Factor loadings indicate that $Fact_1$ captures the largest portion of shared variance across all statements, with high positive loadings for issues such as deforestation (0.910), resource use (0.907), and transport emissions (0.891). These high loadings suggest that $Fact_1$ reflects a general dimension of concern about the environmental impact of food production. $Fact_2$, while accounting for a smaller proportion of the variance, shows relatively stronger loadings for the statements related to animal treatment (0.320) and pesticide use (0.229), suggesting a secondary dimension possibly linked to ethical concerns in food production. However, the overall strength of loadings for $Fact_2$ is weaker, indicating that it plays a more marginal role. The validity of the results is conditioned by the assumption that the instruments used in the estimation are exogenous. The null hypothesis of the refutability test is that all instruments included in Equation 22 are exogenous. The p-values of the refutability test in all cases are greater than 0.92, which leads to the non-reject of the null hypothesis. Table 20 reports the estimation of the two classes LCM with indicator. Therefore, the allocation function is composed of two additional variables to the observable exogenous variables (sociodemographic). The first is the $EnvironmentalDamage$ indicator, and the second

contains the residuals of the auxiliary regression defined in equation 22.

Table 20: Estimation of the LCM with indicator

Variable	Class 1	Class 2
Main Effects		
ASC	-2.800^{***} (0.271)	0.764 (0.637)
Ecosystem Services	1.285^{***} (0.227)	0.615^{*} (0.343)
Organic	1.535^{***} (0.249)	0.910^{**} (0.452)
Farming for Biodiversity	0.459^{***} (0.155)	-0.066 (0.447)
Farming for Biodiversity + Bee	1.090^{***} (0.152)	-0.322 (0.489)
Farming for Biodiversity + Bee + Net Pollination Index	1.265^{***} (0.163)	0.418 (0.432)
PGI	0.437^{***} (0.081)	0.572^{*} (0.296)
PDO	0.575^{***} (0.172)	-0.306 (0.451)
Price	-0.190^{***} (0.012)	-0.176^{***} (0.037)
Interaction Effects Organic		
Ecosystem Services $\times$ Organic	-1.220^{***} (0.410)	-0.099 (0.348)
Farming for Biodiversity $\times$ Organic	-0.365^{*} (0.192)	0.518 (0.461)
Farming for Biodiversity + Bee $\times$ Organic	-0.526^{***} (0.191)	0.286 (0.455)
Farming for Biodiversity + Bee + Net Pollination Index $\times$ Organic	-1.144^{***} (0.209)	0.071 (0.447)
Interaction Effects PDO		
Ecosystem Services $\times$ PDO	-0.054 (0.161)	0.292 (0.338)
Farming for Biodiversity $\times$ PDO	0.570^{***} (0.182)	0.382 (0.487)
Farming for Biodiversity + Bee $\times$ PDO	-0.199 (0.206)	1.082^{**} (0.502)
Net Pollination Index $\times$ PDO	-0.307 (0.236)	0.858^{*} (0.512)
Treatment Effects		
ASC $\times$ Information	-0.769^{**} (0.301)	-1.721^{***} (0.541)
Ecosystem Services $\times$ Information	-0.158^{**} (0.075)	-0.947^{***} (0.284)
Organic $\times$ Information	0.055 (0.080)	-0.257 (0.340)

Continues on next page

Table 20: Estimation of the LCM with indicator (continued)

Variable	**Class 1**	**Class 2**
Farming for Biodiversity × Information	0.026 (0.124)	−0.605 (0.407)
Farming for Biodiversity + Bee × Information	0.025 (0.128)	0.003 (0.449)
Farming for Biodiversity + Bee + Net Pollination Index × Information	0.222* (0.124)	−0.646* (0.389)
PGI × Information	−0.079 (0.109)	−0.370 (0.356)
PDO × Information	−0.091 (0.107)	−0.807** (0.385)
Parameter of the Class 2 Allocation Function		
Constant		−2.159*** (0.759)
Female		0.268 (0.258)
Age		0.355*** (0.093)
Education		0.030 (0.208)
Income		0.167 (0.130)
Full-Time Employment		0.030 (0.273)
Household Size		−0.295*** (0.104)
Children in Household		1.098*** (0.315)
Environmental damage		−0.251*** (0.075)
residuals		0.258* (0.142)

Note: *, **, *** indicate 10%, 5%, 1% significance level, respectively.
Standard deviations of the estimated parameters are shown in parentheses.

First, it's interesting to note that the coefficient associated with the residuals in the allocation function is significant, showing that the $EnvironmentalDamage$ indicator is endogenous. Second, the coefficient of the indicator is negative and significant (-0.251; p-value ≤ 0.000). This points to the fact that individuals' attitudes of concern toward the role of the agribusiness supply chain in damaging the environment through overuse of land and water have significance in distinguishing groups (Hess et al., 2013; Mariel and Arata, 2022). A lower score for this indicator increases the likelihood of belonging to class 2. This is in

line with the result that WTP values for the adoption of ES-related labels are lower in class 2 (Table 21) (Califano et al., 2025). Class 2 is thus characterized by less interest in the proposed labeling and less concern about whether food production has a negative impact on the environment. The model distinguishes two distinct behavioral profiles. Class 1, in which there is a higher probability of belonging accounting for about 82.5 percent of the sample, displays a clear preference for the purchase alternatives presented in the experiment. This is reflected in the negative and significant ASC, suggesting that these respondents value the attributes of the alternatives and actively engage in trade-offs. The probability of belonging to this class increases as age decreases, if no children are present in the household, and if the attitude of concern about the environmental impact of food production supply-chain increase. Class 2 represents a smaller segment that prefers generic information labels, is price sensitive, and is not interested in additional information. For a detailed comparison we report the WTP values (Table 21) recognizing the marginal utility of the two groups with respect to the specific information levels, the interaction between logos and the information treatment outside the labels.

Table 21: Estimation of WTP values

Variable	**Class 1**	**Class 2**
Main Effects		
ASC	-14.748^{***} $[-17.197, -12.299]$	4.342 $[-3.903, 12.587]$
Ecosystem Services	6.767^{***} $[4.281, 9.253]$	3.495^{*} $[-0.520, 7.510]$
Organic	8.084^{***} $[5.442, 10.725]$	5.171^{*} $[-0.204, 10.546]$
Farming for Biodiversity	2.417^{***} $[0.829, 4.006]$	-0.375 $[-5.348, 4.598]$
Farming for Biodiversity + Bee	5.741^{***} $[4.165, 7.316]$	-1.829 $[-7.311, 3.653]$
Farming for Biodiversity + Bee + Net Pollination Index	6.662^{***} $[4.933, 8.390]$	2.376 $[-2.436, 7.189]$

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Table 21: Estimation of WTP values (continued)

Variable	Class 1	Class 2
PGI	2.300^{***} $[1.427, 3.173]$	3.252^{*} $[-0.272, 6.776]$
PDO	3.030^{***} $[1.232, 4.827]$	-1.737 $[-6.906, 3.432]$
Interaction Effects Organic		
Ecosystem Services × Organic	-6.423^{***} $[-10.728, -2.118]$	-0.562 $[-4.461, 3.338]$
Farming for Biodiversity × Organic	-1.924^{*} $[-3.899, 0.051]$	2.947 $[-2.168, 8.062]$
Farming for Biodiversity + Bee × Organic	-2.770^{***} $[-4.702, -0.838]$	1.628 $[-3.452, 6.709]$
Farming for Biodiversity + Bee + Net Pollination Index × Organic	-6.022^{***} $[-8.102, -3.943]$	0.406 $[-4.584, 5.395]$
Interaction Effects PDO		
Ecosystem Services × PDO	-0.285 $[-1.957, 1.386]$	1.659 $[-2.164, 5.482]$
Farming for Biodiversity × PDO	3.000^{***} $[1.086, 4.915]$	2.174 $[-3.415, 7.762]$
Farming for Biodiversity + Bee × PDO	-1.046 $[-3.159, 1.068]$	6.148^{*} $[-0.328, 12.625]$
Farming for Biodiversity + Bee + Net Pollination Index × PDO	-1.619 $[-4.055, 0.817]$	4.874 $[-1.427, 11.175]$
Treatment Effects		
ASC × Information	-4.050^{**} $[-7.237, -0.862]$	-9.781^{***} $[-16.336, -3.227]$
Ecosystem Services × Information	-0.834^{**} $[-1.620, -0.048]$	-5.383^{***} $[-8.958, -1.808]$
Organic × Information	0.288 $[-0.535, 1.111]$	-1.461 $[-5.235, 2.313]$
Farming for Biodiversity × Information	0.138 $[-1.143, 1.419]$	-3.436 $[-8.094, 1.222]$

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Table 21: Estimation of WTP values (continued)

Variable	Class 1	Class 2
Farming for Biodiversity + Bee × Information	0.131 [−1.188, 1.451]	0.020 [−4.977, 5.016]
Farming for Biodiversity + Bee + Net Pollination Index × Information	1.168* [−0.115, 2.450]	−3.674 [−8.110, 0.762]
PGI × Information	−0.417 [−1.542, 0.707]	−2.104 [−6.097, 1.888]
PDO × Information	−0.480 [−1.583, 0.623]	−4.588** [−9.064, −0.111]

Note: *, **, *** indicate 10%, 5%, 1% significance level, respectively.
Lower and upper limits of the 95% confidence intervals are given in square brackets.

Class 1 demonstrates consistently higher and statistically significant WTP values across most sustainability attributes, while Class 2 shows lower and often statistically not significant valuations, consistent with a more price-sensitive and information-averse profile. Class 1 exhibits robust positive preferences for Organic production (8.084, p $\leq$ 0.000) and the generic ES provision logo (6.767, p $\leq$ 0.000). For the specific ES the first information level Farming for biodiversity presents a WTP of 2.417 (p $\leq$ 0.000), while the addition of increased information levels further increases WTP, with Farming for Biodiversity + Bee (5.741, p $\leq$ 0.000) and Farming for Biodiversity + Bee + Net Pollination Index (6.662, p $\leq$ 0.000) both yielding highly significant effects. Geographical Indications (PGI: 2.300, p $\leq$ 0.000; PDO: 3.030, p $\leq$ 0.000) are also positively valued. In contrast, Class 2 values are lower and more varied. In relation to main effects, this group shows that they exclusively prefer the generic level of ES provision (3.495, p $<$ 0.1) and Organic certification (5.171, p $<$ 0.1), but their confidence intervals include zero, suggesting weaker statistical reliability. Interaction effects with Organic reveal important halo effects in Class 1. Ecosystem Services × Organic (–6.423, p $\leq$ 0.000), Farming for Biodiversity × Organic (–1.924, p $<$ 0.1), Farming for Biodiversity + Bee × Organic (–2.770, p $\leq$ 0.000) and Farming for Biodiversity

+ Bee + Net Pollination Index × Organic (–6.022, $p \leq 0.000$), are all significantly negative. These interactions suggest that when the Organic logo is present, the additional value of ES labels diminishes, possibly due to consumer perception that organic production already subsumes these environmental benefits (Jean et al., 2025). In Class 2, none of the Organic-based interactions are significant, implying the absence of such a halo effect in this group. PDO interactions provide mixed results. In Class 1, Farming for Biodiversity × PDO is positive and highly significant (3.000, $p \leq 0.000$), supporting the idea that biodiversity attributes gain credibility when paired with PDO. Other PDO interactions are not insignificant. Treatment effects from information provision show divergent impacts across classes. In Class 1, Ecosystem Services × Information is negative (–0.834, $p < 0.05$), while Farming for Biodiversity + Bee + Net Pollination Index × Information is positive (1.168, $p < 0.1$). This suggests that in this group, the external information layer, which introduces a specificity of service measurement information, increases WTP only in the case of the introduction of the Net Pollination index, while decreasing the marginal utility for the generic ES supply logo. For Class 2, the effect of Ecosystem Services × Information is highly negative (–5.383, $p \leq 0.000$). These consumers respond poorly to additional information, reflecting skepticism or confusion towards detailed environmental claims. The PDO × Information interaction is also negative and significant (–4.588, $p < 0.05$), suggesting that even established quality cues may lose value when overloaded with information.

4.5 Discussion and Conclusions

This study explored the potential of ES-related labels to influence consumer preferences in the food system, using EVOO as a case study. The analysis contributes to the growing literature on sustainable food labeling by assessing how varying label designs and levels of informational detail shape consumer choices. In addition, the moderating role of an external informational treatment, designed to simulate a public awareness campaig, was examined

to evaluate whether providing contextual information enhances consumer valuation of ES. The LCM estimates identified two distinct consumer segments with significantly different preferences. First group showed consistently strong preferences for sustainability attributes. These consumers demonstrated a WTP for a range of ES-related labels, with higher values associated with increasing levels of specificity, from general references to biodiversity, to a visual indicator (bee image), and ultimately to a quantified scientific metric (Net Pollination Index). This group exhibited high engagement with sustainability themes and responded positively to detailed, transparent information (Borrello et al., 2021; Johnson and Geisendorf, 2022). In contrast, a minority segment, displayed lower WTP values and limited responsiveness to detailed ES labels, regardless of the external informational treatment. This group tended to be older, more likely to have children at home, and less concerned about the environmental impacts of food production. Their choices suggest greater price sensitivity and a preference for generic information level, indicating a degree of disengagement or skepticism towards detailed environmental labeling. The inclusion of the external informational treatment produced differentiated effects across segments. While self-reported and objective knowledge levels did not vary substantially between treated and untreated respondents, preferences modeling indicated that the additional information enhanced WTP in the most involved segment. For this group, the treatment acted as a reinforcing mechanism, validating the relevance of ES-related claims and amplifying consumer trust and valuation. This finding suggests that supplementary communication tools—such as in-store educational materials, QR codes linking to explanatory content, or public campaigns—may increase the effectiveness of ES related labels, particularly when targeted at already receptive consumers (Marchi et al., 2024). However, the treatment had no observable effect on the more skeptic group (Casati et al., 2023). This is consistent with findings in the behavioral economics and psychology literature, which highlight that information-based interventions may fail when not aligned with individuals' values, motivations, or perceived relevance (Grunert et al., 2014;

Reisch and Sunstein, 2016). For this segment, information alone is insufficient to modify behavior, pointing to the potential need for alternative strategies, such as more intrusive policy tools related to prices. One of the key findings is the importance of label specificity in driving consumer preferences. The highest WTP was recorded for the most detailed labeling option ("Farming for Biodiversity + Bee + Net Pollination Index"), indicating that consumers value clarity, credibility, and precision in sustainability communication. The inclusion of visual and quantified elements improved perceived product quality and producer trustworthiness (Aprile and Punzo, 2022). These results suggest that vague or generic sustainability claims may be less effective, whereas detailed, verifiable, and visually engaging labels are more likely to influence consumer behavior. Nonetheless, attention must be paid to potential information overload or attribute redundancy. The observed negative interaction between organic certification and ES labels among Class 1 respondents suggests a possible halo effect, whereby the presence of multiple overlapping sustainability claims may dilute the perceived incremental value of additional labels (Janßen and Langen, 2017). This underscores the importance of coherent and complementary label design, where different claims are clearly differentiated in terms of meaning and function (Fresacher and Johnson, 2023). From a policy perspective, the results point to the potential of ES labeling strategies, particularly those linked to measurable environmental outcomes, to stimulate market-based incentives for biodiversity conservation and other ES. As agricultural systems play a dual role in contributing to and mitigating environmental degradation, enhancing the visibility of their environmental contributions through credible labels could serve as a promising lever for sustainable consumption. The heterogeneity in consumer responses also suggests the need for differentiated policy approaches. For highly engaged consumers, information-based nudges and detailed labeling schemes may be sufficient to drive behavioral change. For more disengaged segments, however, regulatory tools, price mechanisms, or default options may be necessary to shift preferences. Policymakers should therefore consider hybrid frameworks that combine voluntary and mandatory

elements, tailored to different levels of consumer engagement (Huang et al., 2024). Several limitations of the study should be noted. First, while the DCE included measures to mitigate hypothetical bias and the econometric approach is based on managing respondents' latent attitudes (Czajkowski et al., 2017b), external validity remain low. Future research should validate these findings using incentivized experiments or observational data. Second, the analysis focused on EVOO, a culturally salient product in the Italian context; generalizability to other products or countries may be limited. Finally, the study did not examine interactions between ES labels and other marketing elements such as branding or packaging, which may influence consumer interpretation and valuation. In conclusion, the results demonstrate that ES-related food labeling can influence consumer preferences, particularly when labels are specific, visual, and supported by credible information. While most consumers are willing to reward sustainability efforts with price premiums, a notable minority remains unresponsive to information-based strategies. To enhance the market uptake of ES-related labels and their contribution to sustainability goals, future interventions should account for the diversity of consumer motivations, the design of complementary communication strategies, and the broader policy environment in which labeling initiatives are embedded.

5 Indirect and Non-use Benefits of Biodiversity in System of National Accounts: a Discrete Choice Experiment and Integration into a Simulated Exchange Value Approach

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Abstract

Integrating biodiversity-related ecosystem services into the System of Environmental Economic Accounting–Ecosystem Accounting remains challenging, particularly for non-market services that generate indirect or non-use benefits. Traditional non-market valuation methods often produce welfare measures, such as consumer surplus, which are incompatible with accounting rules that focus on exchange values. This study develops and tests a novel valuation framework that combines discrete choice experiments with simulated exchange values to address this gap. Employing a latent class model to capture social heterogeneity and modeling stock-dependent willingness to pay via quadratic utility specifications to reflect scarcity effects, the approach allows for pluralistic valuation while producing standardized, policy-relevant accounting metrics. We apply this approach to urban parks in Brescia, Italy, surveying 418 residents to evaluate a program to improve five biodiversity-related ecosystem services. Results reveal distinct preference patterns across population segments, with education, income, and social norms significantly influencing class membership and valuation. The framework effectively translates these heterogeneous preferences into

exchange values compatible with national accounting standards. Findings support the practical implementation of ecosystem accounting in urban contexts and offer actionable insights for policymakers aiming to incorporate biodiversity values into environmental planning and decision-making processes.

Keywords: Simulated exchange value; Biodiversity conservation; System of National Account; Latent class; Social norms

JEL Classifications: C83, C25, Q17.

5.1 Introduction

The System of Environmental Economic Accounting-Ecosystem Accounting (SEEA EA) is a statistical framework that integrates environmental and economic information (United Nations, 2025; Edens et al., 2022). It captures the contribution of ecosystem assets and services to standard measures of economic activity and extends the System of National Accounts (SNA) by including non-market ecosystem goods and services (Hein et al., 2020b). SEEA EA adopts an explicit ecosystem perspective, linking ecosystem extent, condition, and services to economic sectors and tracking changes in ecosystem assets and service flows over time. The United Nations Statistical Commission adopted the SEEA EA in March 2021, marking an important step toward globally consistent ecosystem accounting.

Despite these advances, significant challenges remain. Monetary valuation of ecosystem services (ES) is still difficult, particularly for services that generate indirect or non-use benefits (Pearce and Turner, 1989; Robinson et al., 2022; Scheufele et al., 2025). Economic theory distinguishes between use and non-use values (Krutilla, 1967). Non-use values, including existence and bequest values (Madariaga and McConnell, 1987), are socially relevant but often fall outside standard accounting boundaries. As a result, incorporating these benefits

into ecosystem accounts remains conceptually and practically complex.

SEEA EA requires the use of exchange values. These values represent the prices at which ES would be traded in a hypothetical competitive market and exclude consumer surplus (United Nations, 2025; Caparrós et al., 2017). Most non-market valuation methods, including contingent valuation and discrete choice experiments (DCEs), produce welfare measures that include consumer surplus (Campos et al., 2019; Caparrós et al., 2003). This mismatch limits the integration of non-market ES, as those linked to biodiversity, into core ecosystem accounts (Grilli et al., 2022; Scheufele et al., 2025). As a result, many of these services appear only in supplementary tables.

The Simulated Exchange Value (SEV) method offers a solution. SEV uses demand information, often derived from stated-preference studies, and combines it with supply assumptions to simulate competitive market conditions (Caparrós et al., 2017; Oviedo et al., 2016). It produces exchange values consistent with SNA and SEEA EA. Recent work highlights the potential of embedding DCE-derived willingness to pay (WTP) functions within SEV (Scheufele et al., 2025). Yet practical barriers persist. Many DCEs focus on marginal changes and hypothetical scenarios (Mariel et al., 2021, 2025). They also often rely on simulated, rather than observed, ES quantities (Scheufele et al., 2025). These issues reduce compatibility with accounting needs.

A second challenge concerns pluralistic valuation. SEEA EA recognises that monetary values cannot encompass all value dimensions. The literature calls for approaches that incorporate economic and socio-cultural values without collapsing them into a single metric (Geneletti et al., 2020; La Notte et al., 2019; Hein et al., 2020a). This need is especially strong in urban contexts, where ES demand is heterogeneous and shaped by socio-economic differences and social norms. Urban studies show that monetary indicators alone cannot represent inequalities in access, unmet needs, or socially embedded perceptions of environmental quality (Geneletti et al., 2020; Cortinovis et al., 2021). Pluralistic valuation therefore requires

methods able to reflect social heterogeneity in a structured and transparent way.

This study responds to these gaps. We develop an SEV framework that uses DCE-derived demand functions and links them to observed ES supply. The model accounts for stock dependence and the ecological conditions driving urban ES flows. We incorporate social heterogeneity through a latent-class specification that distinguishes preferences based on income, education, household structure, social norms and information related to biodiversity (Hess et al., 2013; Czajkowski et al., 2015, 2016). This allows us to integrate socio-cultural determinants directly into a monetary measure that complies with SEEA EA principles. It also aligns with recent calls for pluralistic approaches that retain distinct value systems within valuation processes.

To address respondents' limited familiarity with biodiversity-related ES, we define DCE attributes as percentages of site-specific ecological potential. This approach builds on advances in soil science (Vogel et al., 2019; Bartkowski et al., 2022). It clarifies ecological processes, improves understanding of trade-offs, and yields marginal values that are comparable across sites. It also distinguishes between current benefits, unrealised potential, and unmet needs (La Notte et al., 2017; Babí Almenar et al., 2025).

The objective of this paper is to operationalise a valuation framework that integrates pluralistic, socially differentiated information into an exchange-value metric aligned with SEEA EA. We estimate simulated market prices for biodiversity-related urban ES and assess how socio-economic characteristics, knowledge, and social norms shape demand. Through this approach, we contribute to the methodological discussion on aligning secondary and non-use benefits with national accounting and provide empirical evidence supporting the use of SEV in ecosystem accounts and urban policy.

5.2 Literature review

Recent work has considerably broadened the set of applications of the SEV method while clarifying the requirements for its consistency with the SNA.

Early pilot applications focused on nature-based recreation under alternative market structures. For iconic recreational sites, Caparrós et al. (2017) estimated SEVs under monopolistic competition, building on earlier work assuming monopoly pricing (Caparrós et al., 2003) and studies comparing perfect competition and monopoly as lower and upper bounds for simulated prices (Campos and Caparrós, 2006). These applications demonstrate that simplified approaches, such as using the median WTP of 50% of visitors, can approximate full SEV estimations when costs are constant, and that SEVs are more robust than welfare measures to assumptions about the tails of WTP distributions. The SEV framework has also been extended to regulating services, notably air quality. Hein et al. (2016) introduced the maximum societal revenue (MSR) measure, defined as the revenue-maximizing combination of a fee and the number of individuals willing to pay it. MSR is formally equivalent to a SEV and is argued to be well suited for national accounting because it preserves consistency with exchange-value logic.

In addition to recreation and air quality, applications increasingly explore biodiversity and other non-use services. Drawing on DCEs, researchers have demonstrated that SEVs can be estimated for threatened species through the simulation of payment-for-ecosystem-services schemes, even when such schemes do not currently exist, by identifying the maximum payment that could be internalized in a hypothetical market (Campos et al., 2019; Scheufele and Pascoe, 2023). However, further methodological development is required to clarify the conditions under which SEVs can be robustly applied to biodiversity and other services dominated by non-use values (Markandya et al., 2022).

To date, only a limited number of case studies have estimated the exchange values of ES through a simulated market structure. Caparrós et al. (2003) calculated the exchange value

of pine forests in the Guadarrama Mountains (Spain) as the median WTP for unspecified protection measures, obtained through an open-ended contingent valuation. Campos et al. (2019) applied a DCE to assess the exchange value of landscape and threatened biodiversity conservation. The corresponding exchange price was determined as the revenue-maximizing simulated price derived from the estimated mixed logit probability function. This DCE-based SEV approach was also employed by La Notte et al. (2021) to estimate the exchange value of habitat and species maintenance services. Grilli et al. (2022) used a DCE among residents of eastern England to elicitate preferences related to salt marsh management and simulated exchange values, linking them to actual ecosystem conditions. Unlike Campos et al. (2019) and La Notte et al. (2021), Scheufele et al. (2025) propose that the observed quantity in a specific accounting period represents the actual supply for determining the exchange price. They first identify the exchange quantity—using data from extent and condition accounts—and then derive the exchange price by inserting this observed quantity into a DCE-based marginal benefit (demand) function.

To our knowledge, we are the first to present a DCE model that has been adapted so that the marginal estimates of WTP for individual attributes include the latent structure of the social context. These estimates can then be used directly to calculate exchange values.

5.3 Material and methods

5.3.1 Survey and Discrete Choice Experiment Design

Between March and May 2025 questionnaire data were collected with a stated preference survey administered to citizens resident in the city of Brescia, Italy, by a pooling company. The response rate was 14%, with a final sample of 418 respondents.

The questionnaire was structured into four main sections. The first section investigated awareness of needs, awareness of consequences, ascription of responsibility, and personal and

social norms in relation to biodiversity in Brescia's urban parks. The second section contained the DCE. The third section investigated knowledge and understanding of the information provided, and park usage habits, with specific true/false quizzes. The last section, with socio-demographic questions, concluded the questionnaire.

The attributes included in the DCE were selected based on the Common International Classification of Ecosystem Services (CICES) (Haines-Young and Potschin-Young, 2018) for ES provided by urban parks and on the SEEA EA framework for indirect and non-use value assessment. The selection was further informed by literature and expert consultation, following the approach adopted in soil-focused valuation studies (Vogel et al., 2019; Bartkowski et al., 2022; Paul et al., 2021). The starting point was the set of key soil-plant system functions, such as nutrient cycling, water and carbon storage, and habitat provision, which underpin a wide range of ES (Vogel et al., 2019).

Based on iterative consultation with soil scientists, and considering (i) the need for a clear and measurable linkage to soil and plants biodiversity, (ii) relevance for the general population and local administrations, and (iii) independence across attributes, five biodiversity-related ES were identified for the DCE: flood control, disease control, provision of clean drinking water, CO_2 sequestration, and pollinator habitat. These ES capture secondary and non-use benefits of biodiversity in urban parks and are functionally connected to soil microbial and plant diversity. Each attribute was framed as a relative improvement over the current measured state and linked to the maximum potential performance of the environmental asset (Table 22).

Respondents evaluated two scenarios: a status quo (no intervention) and an improvement option describing percentage increases in the five ES. The cost attribute was expressed as an additional annual municipal tax, calibrated to existing park maintenance expenditures provided by the Municipality of Brescia.

In designing the DCE, we initially developed an optimal orthogonal-in-the-differences design. This was used in a pilot study involving a sample of 50 students. Subsequently,

Table 22: Attributes, Levels, Descriptions, and Information on Interventions used in the Discrete Choice Experiment

Attribute	**Levels**	**Description**	**Intervention**
Flood control	10%, 40%, 70%, 100% of the potential	Increase in rainfall infiltration capacity of urban soils during extreme events.	Implementation of rain gardens—shallow, vegetated depressions that collect rainwater and reduce runoff.
Disease control	20%, 40%, 60%, 80% of the potential	Reduction in pathogen spread through improved soil microbial regulation.	Strategies to bioregulate soil microbial communities, stabilizing ecological niches and limiting pathogen vectors (Schierstaedt et al., 2020).
Clean drinking water	25%, 50%, 75%, 100% of the potential	Reduction of chemical pollutants in groundwater via soil filtration.	Bioretention areas treating the first flush of stormwater; pollutant removal enhanced by soil microorganisms (Vogel et al., 2019) and hyperaccumulator plants.
CO_2 sequestration	40%, 60%, 80%, 100% of the potential	Increase in annual CO_2 absorption by vegetation and soils.	Use of specific vegetation (e.g. *Platanus hybrida*) and agronomic practices to enhance carbon storage in soils and plant–soil systems (Barthod et al., 2021).
Pollinator habitat	20%, 40%, 60%, 80%, 100% of the potential	Increase in pollinator visitation rates in urban green areas.	Creation of pesticide-free, plant-diverse habitats with year-round flowering plants, shrubs, and trees.
Additional household tax (€/year)	15; 30; 45; 60; 75; 90	Annual municipal tax to support biodiversity improvements in Brescia's parks.	Monetary contribution to finance the above environmental interventions.

we used the parameters obtained from the pilot study to inform a Bayesian average D-error minimizing efficient design (Scarpa and Rose, 2008; Bliemer and Rose, 2011, 2010; Rose and Bliemer, 2013a). Design simulations were run with 500 Halton draws producing an average D-error of 0.036, on a design with 80 choice tasks. From 80 choice sets 8 choice cards were randomly picked for each respondent, who then evaluated 8 scenarios. Each scenario included an intervention option of improving biodiversity-related ES and an option of non-intervention, resulting in a binary response to ensure incentive compatibility (Carson and Groves, 2007; Collins and Vossler, 2009; Czajkowski et al., 2017a). The description of the interventions presented was delivered in multiple formats: it was provided in written form before the choice experiment and explained orally during the push-to-web telephonic survey's presentation phase.

5.3.2 Econometric Approach

Choice data were analyzed using a Latent Class Model (LCM). LCM is built in the form of a structural equation for the choice model and a class allocation function (Greene and Hensher, 2003b), representing preference heterogeneity by classifying individuals into unobserved classes.

To enable integration with SEV, the utility function was estimated as quadratic in stock levels. The deterministic component of the structural equation is represented as:

$$V_{nit} = ASC_i + x_{nit}\beta_1 + x_{nit}^2\beta_2 + \beta_c Tax \tag{27}$$

where β_1 and β_2 are the linear and quadratic coefficients of the DCE, representing the stock of the ES, and Tax the cost attribute.

Marginal WTP was therefore stock-dependent:

$$wtp(x) = -\frac{\beta_1 + 2\beta_2 x}{\beta_c} \tag{28}$$

This functional form allows us to capture a downward-sloping demand curve, where marginal WTP increases as biodiversity stock becomes scarcer (Scheufele et al., 2025).

Each individual n was then assigned to class q with probability Ψ_{nq}, and conditional on this membership, the probability of choosing alternative i follows a logit form. Specifically, the sequence of choices for individual n is given by:

$$P_n(i \mid q) = \prod_{t=1}^{T} \left(\frac{\exp\left(ASC_i + x'_{nit}\beta_q\right)}{\sum_{j=1}^{J} \exp\left(ASC_j + x'_{njt}\beta_q\right)} \right) \tag{29}$$

The probability of class membership is modeled as:

$$\Psi_{nq} = \frac{\exp\left(\gamma_{0q} + z'_n\gamma_{1q}\right)}{\sum_{q=1}^{Q} \exp\left(\gamma_{0q} + z'_n\gamma_{1q}\right)}, \tag{30}$$

where z_n are observable characteristics. The unconditional probability of a sequence of choices results from weighting equation 29 by equation 30. The number of classes is selected empirically, using information criteria and judgment of model fit.

Endogeneity may arise in the allocation function if unobserved attitudes s_n influence class membership (Mariel and Arata, 2022):

$$F_{nq} = \gamma_{0q} + z'_n\gamma_{1q} + \gamma_{2q}s_n + \xi_{nq} \tag{31}$$

When s_n is endogenous, it can be expressed as:

$$s_n = \alpha_0 + c'_n\alpha_1 + \eta_n, \tag{32}$$

with c_n exogenous variables. Correlation between ξ_{nq} and η_n induces bias. To correct for this, the two-step Control Function approach was applied (Guevara and Polanco, 2016b).

First, s_n was regressed on exogenous and instrumental variables:

$$s_n = \alpha_0 + z_n'\alpha_1 + \alpha_2 Instr_{1n} + \alpha_3 Instr_{2n} + \alpha_4 Fact_{1n} + \alpha_5 Fact_{2n} + \eta_n \tag{33}$$

$Fact_{1n}$ and $Fact_{2n}$ are two additional instruments formed by twelve statements on awareness of need, awareness of consequences, ascription of responsibility, and personal norms related to biodiversity degradation in urban parks in Brescia collected and used to define the two main factors from an exploratory factor analysis. Residuals $\hat{\eta}_n$ were then included in the allocation function:

$$F_{nq}^{CF} = \gamma_{0q} + z_n'\gamma_{1q} + \gamma_{2q} s_n + \gamma_{3q}\hat{\eta}_n + \xi_{nq} \tag{34}$$

To verify the necessary condition that the instruments used in Equation 33 are exogenous, the test of refutability of instrument exogeneity was used (Guevara, 2018). The test is based on the condition of overidentification and first estimates the LCM using Equation 34 in the allocation function, then recalculates the model with a modified allocation function that includes Equation 34 with all instruments except one.

This framework was used to estimate the LCM by including social norms such as attitudes toward biodiversity improvements in Brescia's urban parks.

5.3.3 Transitional Stock Dependence

In the DCE, ES were not presented as instantaneous changes. The scenarios described transitions from the current stock level to a future level reached gradually over a fixed horizon of Y years. This reflects a realistic ecological process: under a business-as-usual trajectory, stock levels decline progressively; under an improved management option, the decline is mitigated or fully offset over the same period. Respondents therefore evaluated changes as unfolding over time, not as abrupt shifts occurring between two consecutive years.

This framing avoids presenting respondents with implausible scenarios. Instant losses or instant improvements are rarely credible for ecosystem processes. Management actions require time to take effect, and degradation typically develops slowly.

The design also used annual payments that lasted for the full duration of the benefit stream. Payments and benefits thus coincided over Y years. Respondents' WTP captured both components of the transition: the avoided loss represented by the difference between the status-quo and the improved trajectory, and the incremental gains occurring as stocks stabilise or improve. The elicited WTP is therefore a cumulative measure that reflects the entire flow of improvements over the transition period.

However, SEEA-EA requires exchange values for a fixed accounting period, usually one year. The valuation must correspond to the benefit of avoiding a stock loss in year t, not to the total benefit of preventing a decline over many years. Thus, the conventional WTP derived from a transitional DCE overestimates the per-period value required for accounting purposes. A correction is needed to translate the cumulative annual WTP into the constant per-unit value of a one-year change in stock level.

To obtain this corrected value, following Scheufele et al. (2025) we equate the present value (PV) of the observed annual WTP, wtp_{or}, with the PV of the benefit stream implied by the ecological transition, $PV(B)$. The term wtp_c denotes the corrected WTP corresponding to a one-unit change in stock level in year t:

$$PV(wtp_{or}) = \sum_{t=1}^{T} \frac{wtp_{or}}{(1+r)^t}, \tag{35}$$

$$PV(B) = \sum_{t=1}^{T} \frac{wtp_c \left(\frac{t-1}{T} + \frac{1}{2T}\right)}{(1+r)^t}. \tag{36}$$

Solving for wtp_c yields:

$$wtp_c = \frac{wtp_{or}[(1-(1+r)^{-T})/r]}{\sum_{t=1}^{T}\left(\frac{t-1}{T}+\frac{1}{2T}\right)/(1+r)^t}. \tag{37}$$

When marginal WTP depends on the stock level, the corrected value becomes:

$$wtp_c(Q) = \frac{(\beta_1 + 2\beta_2 Q/\beta_c)\left(1-\frac{1}{(1+r)^T}\right)/r}{\sum_{t=1}^{T}\frac{(\frac{(t-1)}{T}+\frac{1}{2T})}{(1+r)^t}}. \tag{38}$$

In both cases, the discount rate r ensures comparability across years. This correction produces a WTP consistent with the SEEA-EA requirement that ES be valued for a fixed accounting period. It aligns the DCE output with accounting needs while respecting the ecological realism embedded in the transitional framing.

5.3.4 Simulated Exchange Value

Once the corrected WTP for a one-unit change in stock level is obtained, it can be used to derive the simulated exchange value. The SEV approach treats $wtp_c(Q)$ as the implicit exchange price that would prevail under competitive market conditions. This follows the logic of SEEA-EA, which requires exchange values aligned with SNA conventions and excludes consumer surplus.

The exchange price is given by:

$$p = wtp_c(Q). \tag{39}$$

The exchange value of the ecosystem service flow is:

$$V = Q \cdot p. \tag{40}$$

This value represents the full market-equivalent value of the service flow under the assumption of competitive pricing. Intermediate operational costs must then be subtracted. In the empirical application, these costs correspond to park maintenance expenditures reported by the Municipality of Brescia. Removing these costs yields the net exchange value of the service:

$$V_{ES} = V - C. \tag{41}$$

This value is consistent with the production boundary of SEEA-EA and allows the ES to be integrated into supply and use tables. It reflects the price that would have been observed if biodiversity-related services were traded in a real market, under the assumption that the observed ecological conditions and management interventions constitute the supply.

Finally, the stock value of the ecosystem asset is obtained by discounting future flows of V_{ES} over T years:

$$V_A = \sum_{t=1}^{T} \frac{V_{ES}}{(1+r)^t}. \tag{42}$$

This converts the service flow into an asset value consistent with the SEEA-EA asset boundary. It expresses the contribution of biodiversity-related services as a stock of future benefits, valued at exchange prices, net of intermediate costs, and discounted to reflect time preferences.

This approach ensures that secondary and non-use benefits of biodiversity in Brescia's parks are expressed in exchange-values compatible with SEEA-EA. At the same time, it provides monetary indicators that local administrators can use for planning, budgeting, and evaluating restoration or conservation interventions.

5.4 Results

5.4.1 Descriptive analysis

Data were collected from a sample of 500 respondents residing in the city of Brescia. The final sample consisted of 418 valid responses, representing 3344 observations. Table 23 reports summary statistics for the sociodemographic variables.

The gender distribution is balanced, with a slight predominance of female participants. The age structure is well spread across classes, with the largest shares in the 45–54 and 35–44 groups. Education levels show a concentration in high school and university degrees, while employment status is dominated by full-time workers. The income distribution reflects a broad range of economic conditions, with most respondents falling within the lower and middle income brackets. Household characteristics display moderate household sizes and a low average number of young children. To ensure data quality and representativeness, we applied post-stratification weights, assessed potential non-response bias, and conducted socio-demographic representativeness tests.

Table 24 shows the relative frequency of the scores given by the respondents to the attitudinal questions about the improvements in biodiversity in Brescia's urban parks.

Table 23: Descriptive Statistics

Category	Variable	Mean (SD)[1,2]	Minimum	Maximum
Gender	Female	54.5%	0	1
Age class	Age 18–24	10.4%	0	1
	Age 25–34	21.2%	0	1
	Age 35–44	21.4%	0	1
	Age 45–54	25.7%	0	1
	Age 55–65	14.4%	0	1
	Age 65+	7.0%	0	1
Education	Middle School	13.2%	0	1
	High School	48.9%	0	1
	Bachelor's Degree	14.6%	0	1
	Master's Degree	18.4%	0	1
	Post Graduate	5.0%	0	1
Employment	Inactive	4.8%	0	1
	Unemployed	13.0%	0	1
	Retired	6.2%	0	1
	Part-time	19.6%	0	1
	Full-time	56.5%	0	1
Income class	$\leq$ 18,000€	25.9%	0	1
	18,001–24,000€	23.4%	0	1
	24,001–45,000€	35.3%	0	1
	45,001–65,000€	9.2%	0	1
	$\geq$ 65,000€	6.2%	0	1
Household	Household Size	2.848 (3.823)	1	9
	Children $\leq$14	0.351 (0.667)	0	4
Sample Size	N	418		

[1]For dummy variables, values represent the percentage of respondents in each category

[2] Standard deviation in parentheses for continuous variables

Table 24: Attitudinal questions and relative frequency of the score (1 = strongly disagree; 5 = strongly agree)

Category	Question	1	2	3	4	5
Awareness of need	Compared with other environmental issues of Brescia, biodiversity of urban parks is not a high priority.	13.7%	28.4%	29.1%	22.4%	6.4%
	The current biodiversity condition in Brescia urban parks is sufficient.	7.3%	33.1%	34.8%	22.9%	1.9%
	There is no need to adopt measures to increase biodiversity in Brescia urban parks.	16.2%	39.5%	27.1%	13.9%	3.2%
Awareness of consequences	I am aware of the consequences decreasing biodiversity will have on quality of life in urban areas	2.4%	3.2%	23.1%	53.4%	17.9%
Ascription of responsibility	I feel jointly responsible for conservation of our parks.	2.6%	7.3%	29.1%	44.7%	16.5%
	I feel jointly responsible for the negative consequences of biodiversity degradation in urban parks	5.1%	13.9%	34.4%	30.1%	16.5%
	I believe that every citizen of Brescia is partly responsible for the conservation of our parks	1.9%	5.1%	18.4%	48.9%	25.6%
	I feel joint responsibility for the financial support of biodiversity improvement measures in Brescia	6.2%	12.4%	41.9%	30.1%	9.4%
Personal norm	I feel a moral obligation to financially support improvement/conservation of our parks no matter what other people do.	8.1%	14.3%	39.7%	28.2%	9.6%
	Seen from my values, the right thing to do is to support biodiversity conservation in our city.	1.3%	4.7%	26.3%	49.6%	18.2%
	It would be against my moral principles not to protect biodiversity for the future in our city.	3.2%	4.7%	26.7%	48.3%	17.1%
	People like me should do everything they can to decrease degradation of our park's biodiversity.	2.8%	6.0%	29.3%	47.2%	14.7%
Social norm	My friends and relatives would be in favor of me contributing to increase biodiversity improvement measures	3.2%	5.3%	47.6%	32.3%	11.5%
	Most people who are important to me think I should financially support improvement of biodiversity in Brescia's parks	6.4%	16.7%	46.2%	22.4%	8.3%
	People whose opinions I value would prefer that I support conservation of our parks.	5.3%	8.3%	49.8%	28.0%	8.5%

The distribution of responses across the normative constructs reveals distinctive patterns in public perception towards urban biodiversity conservation. Notably, responses concerning awareness of need demonstrate a pronounced skew towards disagreement, with the majority of respondents rejecting statements that biodiversity is not a priority (41.8% combined disagree/strongly disagree) or that current conditions are sufficient (40.4% disagree/strongly disagree). This suggests a recognized deficiency in current conservation efforts among Brescia's residents.

Conversely, the awareness of consequences and ascription of responsibility domains exhibit strong positive orientation, with 71.3% and 61.2% of respondents, respectively, agreeing or strongly agreeing with statements acknowledging personal responsibility and potential impacts of biodiversity loss. This alignment indicates a cognitively coherent understanding of both the implications of biodiversity degradation and individual accountability.

The personal norm dimension reveals particularly robust internalization of conservation ethics, with 67.8% of respondents affirming moral obligations to support biodiversity protection. However, a notable discrepancy emerges in social norms, where neutral responses predominate (47.6%, 46.2%, and 49.8% across items), suggesting either uncertainty about referent groups' attitudes or weaker social reinforcement mechanisms. This normative misalignment between personal conviction and perceived social expectations may represent a critical barrier to collective action.

5.4.2 Latent Class Model estimation

This section presents the estimates of an LCM that includes the potentially endogenous variable $Socialnorms$ in the allocation function. A single component was initially extracted from the statements on social norms. Then we needed to find appropriate instruments for the auxiliary equation defined in Equation 33. The instruments must be related to the instrumented variable but uncorrelated with the error term in the allocation function. Given

this theoretical setting, the instruments we used are the dummy variable indicating whether the individual lives near a park (time travel $\leq 10minutes$) and the number of visits per year to "their" park. To increase the number and quality of the instruments, we used two additional instruments ($Fact_{1n}$ and $Fact_{2n}$) extracted from the exploratory factor analysis applied to the other twelve statements. The main results of this factor analysis are presented in Table 25.

Table 25: Exploratory Factor Analysis

	Eigenvalues and variability percentages				**Factor loadings**	
	Eigenvalue	**Proportion**	**Cumulative**	**Variable**	**Factor1**	**Factor2**
Factor1	4.317 36	0.565	0.565	aw_need1	−0.2289	0.6263
Factor2	1.603 91	0.2099	0.7749	aw_need2	−0.1251	0.6869
Factor3	0.613 59	0.0803	0.8552	aw_need3	−0.2611	0.6379
Factor4	0.459 84	0.0602	0.9154	aw_cons	0.4751	−0.1422
Factor5	0.198 70	0.0260	0.9414	ascr_resp1	0.7374	0.2697
Factor6	0.154 70	0.0202	0.9616	ascr_resp2	0.6713	0.3256
Factor7	0.138 32	0.0181	0.9797	ascr_resp3	0.6061	0.0872
Factor8	0.083 67	0.0109	0.9907	ascr_resp4	0.7225	0.2115
Factor9	0.065 10	0.0085	0.9992	pers_norm1	0.6932	0.1559
Factor10	0.006 08	0.0008	1.0000	pers_norm2	0.7026	−0.1719
Factor11	0.000 27	0.0000	1.0000	pers_norm3	0.7483	−0.1628
Factor12	−0.000 25	0.0000	1.0000	pers_norm4	0.7332	−0.0345

The factor analysis reveals a clear two-factor solution explaining 77.49% of the total variance. Factor 1 (56.5% variance) shows strong positive loadings from ascription of responsibility and personal norm items. Factor 2 (20.99% variance) is defined by negative awareness of need items. The eigenvalue scree occurs after the second factor ($\lambda \geq 1$). All primary loadings exceed 0.47, demonstrating good simple structure. The pattern suggests two distinct psychological constructs: one related to personal obligation and another to perceived need for intervention.

The estimation of LCM is reported in Table 26. Two distinct groups of respondents emerge, each exhibiting a differentiated structure of preferences for ES.

The first class, representing 43.2% of the sample, assigns relatively higher importance

Table 26: Estimation of the Latent Class Model with indicator

	Class 1 (43.4%)			Class 2 (56.6%)		
Variable	**Coefficient**	**Std. err.**	**P$\geq z$**	**Coefficient**	**Std. err.**	**P$\geq z$**
ASC	-0.651	0.275	0.018^{**}	1.147	0.589	0.052^{*}
Tax	-0.022	0.002	0.000^{***}	-0.019	0.007	0.003^{**}
Linear component						
Flood control	-0.001	0.006	0.820	0.034	0.014	0.016^{**}
Disease control	0.006	0.008	0.448	0.037	0.016	0.019^{**}
Clean drinking water	0.017	0.008	0.024^{**}	0.037	0.017	0.032^{**}
CO_2 sequestration	0.017	0.010	0.085^{*}	0.001	0.019	0.970
Pollinator habitat	0.021	0.008	0.007^{***}	0.044	0.020	0.026^{**}
Quadratic component						
Flood control	0.0001	0.0001	0.287	-0.0003	0.0002	0.064^{*}
Disease control	0.0000	0.0001	0.869	-0.0003	0.0002	0.095^{*}
Clean drinking water	-0.0001	0.0001	0.340	-0.0002	0.0002	0.275
CO_2 sequestration	-0.0002	0.0002	0.181	0.0001	0.0004	0.725
Pollinator habitat	-0.0002	0.0001	0.039^{**}	-0.0004	0.0002	0.098^{*}
Class 1 allocation function						
Female	0.056	0.242	0.818			
Age	-0.009	0.009	0.311			
Education	0.400	0.127	0.002^{***}			
Income	-0.376	0.128	0.003^{***}			
Full time	-0.304	0.263	0.248			
Household	0.168	0.119	0.159			
Children ≤ 14	0.109	0.214	0.611			
Social norms	-1.294	0.209	0.000^{***}			
residuals	1.210	0.267	0.000^{***}			
constant	-0.342	0.772	0.657			

to clean drinking water from water filtration service and pollinator habitat, while displaying only limited support for the remaining services. In contrast, the second class, comprising 56.8% of respondents, places substantial value also on flood control and disease control, with CO_2 sequestration failing to emerge as significant in this local context. The inclusion of quadratic terms further indicates stock-dependent WTP among Class 2 respondents, particularly with respect to flood control, disease control and pollinator habitat services, suggesting that marginal valuations increase as biodiversity stocks decline.

The allocation function parameters highlights the socio-demographic and attitudinal determinants that explain membership in Class 1. Education shows a positive and significant effect, suggesting that more educated respondents are more likely to belong to Class 1. Income has a significant negative effect, indicating that higher-income individuals are less likely to fall into this class. Social norms exert the strongest and most significant influence, with a high negative coefficient, meaning that respondents who consider their community's opinion important when deciding to support biodiversity improvement are much less likely to be assigned to Class 1. The significant residual term confirms the endogeneity of the variable.

5.4.3 WTP and Simulated Exchange Value Estimations

The estimated stock dependent marginal WTP values for a one percentage point improvement in ES provision are reported in Table 27.

The mWTP estimates reveal clear preference heterogeneity across classes. Class 2 displays substantially higher WTP for most services. Both classes assign statistically significant positive values to clean drinking water and pollinator habitat. The presence of quadratic terms indicates non-linear marginal utility, particularly strong for pollinator habitat, consistent with ecological evidence that marginal benefits decline as ecological conditions improve (Bartkowski, 2017; Pascual et al., 2015).

The results support a stock-dependent valuation structure only for pollinator habitat ser-

Table 27: Stock Dependent Observed Marginal Willingness-to-Pay Estimates

mWTP	Class 1 (43.4%)				Class 2 (56.6%)			
	Coef.	Std. err.	95% CI		Coef.	Std. err.	95% CI	
			Low	Up			Low	Up
ASC	-29.157^{**}	13.902	-56.406	-1.909	59.671^{***}	21.771	17.001	102.342
Linear component								
Flood control	-0.036	0.290	-0.634	0.502	1.786^{*}	1.026	-0.229	3.792
Disease control	0.269	0.362	-0.441	0.978	1.941^{*}	1.104	-0.252	4.074
Clean drinking water	0.768^{**}	0.354	0.075	1.461	1.943^{*}	0.991	-0.019	3.866
CO_2 sequestration	0.767^{*}	0.440	-0.115	1.609	0.059	1.008	-1.937	2.014
Pollinator habitat	0.954^{***}	0.358	0.254	1.657	2.313^{**}	0.967	0.367	4.159
Quadratic component								
Flood control	0.003	0.003	-0.003	0.009	-0.015	0.010	-0.035	0.005
Disease control	0.001	0.004	-0.008	0.009	-0.017	0.012	-0.041	0.007
Clean drinking water	-0.004	0.004	-0.013	0.004	-0.012	0.012	-0.035	0.010
CO_2 sequestration	-0.009	0.007	-0.023	0.004	0.007	0.019	-0.031	0.044
Pollinator habitat	-0.009^{**}	0.004	-0.017	0.000	-0.020^{*}	0.011	-0.043	0.002

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Note: ASC = Alternative Specific Constant to entering the program.

Confidence intervals calculated using the delta method.

Abbreviations: Coef. = Coefficient, CI = Confidence Interval, Low = Lower bound, Up = Upper bound.

vice, aligning this ES with theoretical expectations that scarcity increases marginal values (Krutilla, 1967; Madariaga and McConnell, 1987). This result mirrors the patterns observed in other studies of stated preferences for biodiversity and unfamiliar public goods (Aanesen et al., 2015; Robinson et al., 2022). It highlights the importance of clearly measuring the service, such as by counting pollinators, in order to generate stock-dependent demand.

However, the quadratic functional form warrants careful interpretation, as it may generate non-monotonic valuation profiles. For example, flood control in Class 1 exhibits a negative (though statistically not significant) linear coefficient, inducing a negative mWTP estimate. Similar challenges have been identified when using reduced-form valuation functions for soil- and water-related ES (Bartkowski et al., 2022; Paul et al., 2021).

Estimates of the stock dependent WTP and simulated exchange values are presented in Table 28. SEVs were computed using a 5% discount rate over a 20-year horizon. The resulting exchange prices (*Corrected WTP*) reveal differences across ES.

Correcting for stock dependence markedly amplifies the valuation of high-performing services: pollinator habitat exhibits the highest weighted exchange price (Corrected $\text{WTP}_w = 4.027$ €/m^2), followed by clean drinking water (3.379 €/m^2). By contrast, flood control displays strong preference heterogeneity, with Class 1 showing a negative corrected WTP (-0.156 €/m^2). These patterns underscore the sensitivity of regulating ES to class-specific perceptions of risk and benefit, consistent with earlier evidence on socially differentiated valuations (Yao and Wallace, 2024; Failler et al., 2015).

To ensure full compatibility with physical ecosystem accounts, the "stock" variable (Q) must be anchored in measurable biophysical indicators. We therefore propose the following operational definitions which links each ES to its extension in terms of surface area:

- **Flood Control:** Water retention volume (20mm/h m^2) during a standardized extreme rainfall event (45mm/h), consistent with hydrological indicators used in national ecosystem accounts (Hein et al., 2020b).

Table 28: Exchange Prices, Exchange Values and Asset Values for one square meter of current ES stock

Service Description		Observed WTP			Corrected WTP		
		Class 1 (43.4%)	Class 2 (56.6%)	Weighted (w)	Class 1 (43.4%)	Class 2 (56.6%)	Weighted (w)
Service	Stock	(€/m^2)	(€/m^2)	(€/m^2)	(€/m^2)	(€/m^2)	(€/m^2)
Flood Control	0.1	−0.065	1.778	0.956	−0.156	4.232	2.337
Health Control	0.2	0.269	1.904	1.165	0.640	4.533	2.851
Clean Water	0.25	0.766	1.917	1.417	1.823	4.563	3.379
CO_2 Seq.	0.4	0.740	0.044	0.346	1.760	0.104	0.820
Pollinator Hab.	0.2	0.952	2.255	1.674	2.266	5.367	4.027

Part 2: Net Exchange Values with constant Operational Costs (€/m² year)

Service Description		Exchange Value			Net Exchange Value			
		Class 1 (43.2%)	Class 2 (56.8%)	Weighted (w)	Op.Cost	Class 1 (43.2%)	Class 2 (56.8%)	Weighted (w)
Service	Stock	(€/m^2)	(€/m^2)	(€/m^2)	(€/m^2)	(€/m^2)	(€/m^2)	(€/m^2)
Flood Control	0.1	−0.016	0.423	0.234	0.25	−0.266	0.173	−0.016
Health Control	0.2	0.128	0.907	0.570	0.25	−0.122	0.657	0.320
Clean Water	0.25	0.456	1.141	0.845	0.25	0.206	0.891	0.595
CO_2 Seq.	0.4	0.704	0.042	0.328	0.25	0.454	−0.208	0.078
Pollinator Hab.	0.2	0.453	1.073	0.805	0.25	0.203	0.823	0.555

Part 3: Asset Values (€/m² 20-year horizon and 5% discount rate)

Service Description		Asset Values		
Service	Stock	Class 1	Class 2	Weighted
Flood Control	0.1	−3.310	2.159	−0.204
Health Control	0.2	−1.521	8.182	3.991
Clean Water	0.25	2.563	11.101	7.412
CO_2 Seq.	0.4	5.658	−2.597	0.970
Pollinator Hab.	0.2	2.533	10.262	6.923

Note: All monetary values in Euros. Stock = Current stock level (% of potential). Class 1 = 43.2%, Class 2 = 56.8%, w = weighted average. Original WTP = willingness-to-pay before transition correction. Corrected WTP = WTP after stock dependence correction (weighted value corresponds to Exchange Price, EP, in € per 1% improvement). Op. Cost = Operational Cost. Net Exchange Value = Exchange Value - Operational Cost. Asset Value = present value of 20-year Net Exchange Value stream at 5% discount rate.

- **Disease Control:** Soil microbial biodiversity index (QBS soil index) per square meter, reflecting established links between microbial communities and pathogen suppression (Schierstaedt et al., 2020).

- **Clean Drinking Water:** Mass of pollutants (e.g. heavy metals) removed through soil filtration (g/m^2 year), consistent with soil-function evaluations (Vogel et al., 2019).

- **CO_2 Sequestration:** Carbon stocks in soil and biomass (g/m^2), following common carbon-accounting practice (FAO, 2024).

- **Pollinator Habitat:** Pollinator visitation rate (visits/30 min/m^2), a widely used ecological indicator of habitat quality.

Relating Q to measurable biophysical metrics ensures alignment with SEEA-EA condition and flow accounts (Hein et al., 2016; Haines-Young and Potschin-Young, 2018).

Integrating operational costs yields more conservative estimates, with flood control producing a slightly negative weighted net exchange value (-0.016 €/m^2), while clean water and pollinator habitat remain clearly positive (0.595 and 0.555 €/m^2, respectively). When these annual net flows are projected over a 20-year horizon using a 5% discount rate, they generate substantial asset values that reflect the long-term economic contribution of each service. Clean drinking water attains the highest weighted asset value (7.412 €/m^2), closely followed by pollinator habitat (6.923 €/m^2), illustrating how even moderate annual net benefits accumulate into significant stocks of natural capital. Conversely, negative asset values for Class 1 in flood and disease control arise from persistently low or negative net flows, demonstrating how sustained preference patterns translate into diminished long-run economic value. Overall, the temporal dimension of SEV highlights that ES with stable, positive annual returns become major contributors to natural capital, whereas services with weak or contested social demand accumulate limited or negative economic worth.

The results demonstrate that biodiversity conservation may generate substantial economic returns. Moreover, the SEV framework integrates biophysical and economic information into an accounting-compatible structure, contributing to recent efforts to advance natural capital accounting methodologies (Turner et al., 2019; Badura et al., 2023).

5.5 Discussion and Conclusions

This study proposes a methodological pathway for integrating discrete choice experiments (DCEs) within the SEEA-EA framework. The SEV approach addresses a key conceptual challenge by converting WTP measures—which include consumer surplus—into exchange-compatible values. By using a stock-dependent WTP function, the method captures transitional stock effects and anchors monetary values to measurable ecological states. Employing a LCM to estimate initial WTP within an SEV structure is a novel contribution, enhancing the potential to incorporate non-use values into ecosystem accounts (Campos et al., 2022; La Notte et al., 2019).

Several limitations merit consideration. First, some DCE attributes were technically demanding. Framing them as percentages of ecological potential may have imposed cognitive burden, potentially encouraging heuristic decision-making and noisier estimates (Czajkowski et al., 2016). Second, the relatively low response rate (14%) raises concerns about non-response bias, as environmentally engaged individuals may be overrepresented (Czajkowski et al., 2015). Third, SEV estimates rely on strong assumptions. The simulated market structure assumes perfect competition or perfect price discrimination—conditions seldom met for public goods such as ecosystem services (Obst and Vardon, 2014). The choice of a 5% discount rate and a 20-year horizon also affects the magnitude of values, underscoring the need for sensitivity analysis (Ruijs and van Egmond, 2017). Fourth, the stock-dependent WTP was modeled using an ad-hoc quadratic functional form, which may generate non-monotonic or negative WTP estimates, as observed for flood control. More flexible approaches—such as

spline-based or semi-parametric specifications—could provide improved theoretical consistency (Capriolo et al., 2020).

Despite these limitations, the study demonstrates a feasible operational method for aligning non-market valuation with national accounting principles. This advances recent calls to integrate ES valuation into decision-making and national statistical systems (Guerry et al., 2015; Babí Almenar et al., 2025). Future research should further strengthen the link between biophysical ecosystem accounts and economic valuation, explore alternative functional forms for stock-dependent preferences, and conduct extensive sensitivity analyses. Such developments will enhance the policy relevance and robustness of exchange value estimates for biodiversity and ecosystem services.

Conclusions

Making the value of biodiversity and ES visible, measurable and relevant to decision-making within agri-food systems is a central and increasingly urgent challenge at the intersection of economics, ecology and politics. Grounded in the conceptual framework of natural capital accounting and explicitly aligned with the SEEA EA, this thesis develops and integrates a set of empirical and methodological contributions that collectively advance the state of the art in ES valuation, incentive design, and market-based mechanisms for sustainability. The originality of the work lies not only in any single contribution taken in isolation, but also in the way distinct analytical fronts are articulated into a mutually reinforcing research agenda, linking welfare based valuation, accounting compatible monetary measures, behavioral responses of producers and consumers, and policy relevant instruments under conditions of risk and uncertainty.

At a broad level, the thesis responds to the growing recognition, articulated in international policy debates, that prevailing economic metrics and governance frameworks systematically underestimate the contribution of nature to economic performance and human well-being. By focusing on agri-food systems, the research situates this challenge within a sector where natural capital dependencies, environmental externalities, and socio-economic risks converge most sharply. Across five interrelated studies, the thesis contributes original insights into how ecosystem values are generated, perceived, and transmitted through policy instruments, markets, and accounting systems, and how these processes may be improved to support more resilient and sustainable development pathways.

The first major front of contribution concerns the synthesis and interpretation of existing monetary valuations of ES, with particular attention to freshwater ecosystems. The meta-analysis developed in Chapter 1 goes beyond a descriptive aggregation of values by explicitly modeling methodological heterogeneity and testing the robustness of value transfer func-

tions for policy and accounting use. The results confirm the extreme variability of valuation estimates reported in the literature, reflecting differences in ecosystem types, services considered, socio-economic contexts, and valuation methods. However, the analysis makes a more original contribution by demonstrating that, once methodological differences are explicitly accounted for in a meta-regression framework, most valuation approaches do not yield statistically distinguishable effects on estimated values. The notable exception is represented by choice experiment methods, which systematically produce lower value estimates than cost-based and direct market approaches. This finding is highly relevant for both valuation practice and policy interpretation, as it underscores the proxy nature of cost-based methods and highlights the risk of conflating accounting friendly measures with welfare consistent values.

More fundamentally, the meta-analysis reinforces a key conceptual insight that runs throughout the thesis: the bulk of the economic value generated by ecosystems lies outside conventional markets and can only be captured through non-market valuation techniques. Yet these values remain systematically undervalued or excluded from decision-making frameworks, particularly when translated into accounting metrics. By testing the performance of meta-analytic value transfer functions, the study provides empirical evidence that such tools can deliver transfer errors comparable to those reported in other applied contexts, rendering them acceptable, albeit imperfect, inputs for conservation and policy analysis. At the same time, the limitations identified in the meta-analysis, particularly the insufficient treatment of ecosystem quality, spatial substitutes, and service-specific demand and supply characteristics, are not merely technical caveats. They point to a deeper structural challenge in ecosystem valuation: the difficulty of reconciling ecological complexity with the parsimonious representations required for large scale accounting and policy applications. This tension motivates and informs the subsequent contributions of the thesis.

The second and third fronts of contribution shift the analytical focus from ecosystem

valuation per se to the behavioral foundations of policy instruments designed to internalize environmental externalities in agriculture. Chapters 2 and 3 examine farmers' adoption of sustainable practices within the context of CAP eco-schemes, explicitly incorporating risk, uncertainty, and asset structures into DCMs. These chapters jointly advance the literature in two important and complementary ways. First, they provide empirical evidence on how different incentive mechanisms, state subsidies versus market-based biodiversity credits, and governance structures, public versus third-party monitoring, shape farmers' preferences and WTA environmentally beneficial practices. Second, they deepen the theoretical treatment of risk by testing whether farmers integrate background wealth and asset positions into their evaluation of conservation contracts.

The stated choice analysis in Chapter 2 reveals substantial heterogeneity in farmers' WTA incentives for sustainable practices, driven by prior adoption status, regional characteristics, and perceived production risks. The finding that current adopters often require lower incentives, and in some cases are willing to pay to maintain certain practices, highlights the importance of experience, learning, and perceived co-benefits in shaping adoption costs. This result carries a critical policy implication: eco-schemes designed as uniform payments risk financing practices that are already widespread, thereby generating limited additional environmental benefits and inefficient resource allocation. Furthermore, a significant contribution of the chapter lies in demonstrating a clear preference among winegrowers for a biodiversity credit market over traditional subsidy schemes. This preference reflects a willingness to engage with market-based instruments that offer higher expected returns and greater flexibility, provided that credible monitoring and governance structures are in place. In doing so, the analysis challenges the conventional assumption that farmers are primarily subsidy-dependent and risk-averse with respect to environmental innovation, at least in high-value sectors such as viticulture.

Chapter 3 extends this behavioral analysis by addressing a long standing debate in the

economics of risk: whether decision-makers integrate background wealth into their evaluation of risky choices. In line with theoretical expectations and experimental evidence, the study finds no indication that farmers' asset positions influence their experimental choices regarding conservation incentives. This null result is itself a substantive contribution, as it suggests that farmers evaluate eco-scheme participation within a narrow mental account, largely disconnected from long-term wealth considerations or farm viability. From a policy perspective, this finding is particularly salient. It implies that financial incentives alone may be insufficient to alter farmers' perceptions of risk and relevance associated with sustainable practices. Instead, adoption decisions appear to hinge on trust, perceived agronomic fit, and the credibility of factors that contribute to policy commitments that are not captured by monetary compensation alone.

Taken together, Chapters 2 and 3 provide a nuanced and internally consistent picture of farmers as economic agents operating under uncertainty, but with bounded frames of reference. The synergy between these two chapters lies in their joint implication that effective agri-environmental policy cannot rely solely on price signals. While market-based instruments such as biodiversity credits show promise, their effectiveness depends on complementary measures, including advisory services, participatory design, and long-term policy stability. This insight directly connects the behavioral analysis of producers to the broader objectives of natural capital accounting, which seeks not only to measure ecosystem values but also to inform incentive structures capable of sustaining those values over time.

The fourth front of contribution addresses the demand side of ES provision by examining how information and labeling schemes influence consumer preferences and WTP for ES related attributes. Chapter 4 situates itself within the growing literature on sustainable food labeling but advances it in some original respects. First, it explicitly frames ES labels as a potential mechanism for mobilizing private financing for natural capital conservation, thereby complementing public incentives analyzed in earlier chapters. Second, it systematically tests

how different levels of label specificity, from generic biodiversity claims to quantified scientific indicators, affect consumer valuation. Third, it examines the role of external information treatments as a proxy for public awareness campaigns.

The latent class analysis reveals pronounced heterogeneity in consumer responses. A majority segment displays strong preferences for sustainability attributes and assigns increasing value to more specific, transparent, and quantified ES labels. For these consumers, detailed information acts as a trust enhancing signal, reinforcing the credibility of environmental claims and translating into higher WTP. In contrast, a smaller but non negligible segment remains largely unresponsive to detailed information, exhibiting greater price sensitivity and skepticism toward environmental labeling. The finding that external information treatments amplify preferences only among already engaged consumers aligns with insights from behavioral economics regarding motivated reasoning and value congruence.

The originality of this contribution lies not only in documenting these patterns, but in explicitly linking them to policy design. The results suggest that information-based instruments and voluntary labeling schemes can be effective levers for sustainability, but only for specific consumer segments. For more disengaged groups, stronger regulatory or price-based interventions may be required. Moreover, the observed interactions between ES labels and organic certification point to the risk of information overload and halo effects, underscoring the need for coherent and non-redundant label architectures. By situating consumer behavior within the broader framework of ES provision and financing, Chapter 4 complements the producer side analysis and reinforces the thesis's central argument that sustainable agri-food systems require coordinated interventions across the value chain.

The fifth and final front of contribution addresses a core conceptual and methodological challenge in ecosystem accounting: how to translate welfare based measures of ES value into exchange values suitable for inclusion in SNA. Chapter 5 proposes and operationalizes a SEV approach that integrates DCE results into the SEEA EA framework. This contribution

is particularly original in its explicit treatment of stock-dependent preferences, allowing monetary values to be anchored to measurable ecological states and to capture transitional dynamics in ecosystem assets.

By converting WTP measures, which include consumer surplus and non-use values, into exchange values, the SEV approach provides a practical bridge between economic valuation and accounting principles. The use of latent class models within this framework further enhances its ability to incorporate preference heterogeneity, a feature often lost in aggregate accounting exercises. At the same time, the chapter is transparent about the strong assumptions underlying the SEV methodology, including simulated market structures, discount rates, time horizons, and functional forms for stock dependence. Rather than weakening the contribution, this explicit discussion of limitations strengthens its policy relevance by clarifying the conditions under which such values should be interpreted and used.

The significance of this contribution becomes fully apparent when viewed in synergy with the preceding chapters. The meta-analysis of Chapter 1 highlights the prevalence and importance of non-market values, while also revealing the challenges of transferring them across contexts. Chapters 2 to 4 demonstrate how these values are shaped, perceived, and acted upon by producers and consumers under real world constraints. Chapter 5 closes the conceptual loop by showing how such values can be systematically incorporated into accounting systems that inform macroeconomic policy, financial regulation, and sustainability reporting. In this sense, the SEV framework does not stand alone as a technical exercise, but represents the way to reconcile valuation theory, behavioral evidence, and institutional requirements.

Across its five empirical and methodological studies, the thesis thus delivers a set of interlocking contributions that advance the literature on ES economic valuation in some aspects. Individually, each chapter addresses a specific gap: improving the robustness of value transfer, elucidating farmers' risk perceptions and incentive preferences, clarifying the

limits of asset integration in decision-making, identifying the conditions under which ES labels influence consumer behavior, and operationalizing exchange values for ecosystem accounting. Collectively, these contributions generate a richer and more coherent understanding of how ecosystem values can be measured, internalized, and governed within agri-food systems.

From a theoretical standpoint, the thesis reinforces the view that natural capital is not merely an environmental add-on to economic systems, but a foundational asset that shapes production possibilities, risk exposure, and long-term welfare. It also highlights the limits of purely monetary approaches when divorced from behavioral and institutional contexts. From a policy perspective, the findings suggest that effective integration of ES into decision-making requires a diversified instrument mix, combining market-based mechanisms, targeted subsidies, credible information, and robust accounting frameworks.

Several overarching implications emerge. First, improving the visibility of ES in economic statistics is a necessary but not sufficient condition for sustainability. Without instruments that translate measured values into credible incentives and market signals, accounting reforms risk remaining largely symbolic. Second, heterogeneity, in ecosystems, in preferences, and in behavioral responses, is a defining feature of agri-food systems and must be explicitly addressed in both valuation and policy design. Third, risk and uncertainty are central to decisions on both the supply and demand sides of ES provision, yet they are often insufficiently integrated into valuation and accounting exercises. By explicitly incorporating risk perceptions, asset structures, and information effects, this thesis contributes to closing this gap.

As with any empirical and methodological endeavor, the research presented here is subject to several limitations. The meta-analysis, despite its breadth, is constrained by the uneven geographic distribution of studies, with under-representation of certain regions such as the Americas and Oceania. This limits the global generalizability of value-transfer functions and underscores the need for expanding primary valuation research in under-studied areas. Additionally, the meta-analytic approach primarily captures ecosystem extent, whereas ecosystem

condition and quality remain insufficiently addressed due to data limitations. In the farmer-focused studies, the DCEs rely on hypothetical scenarios and self-reported asset data, which may be subject to cognitive burden, heuristic decision-making, and potential measurement error. The moderate sample sizes and regional focus limit the external validity of results across diverse agricultural systems and production contexts. The modeling of stock-dependent risk attitudes, while innovative, employs functional forms that may not fully capture the complexity of subjective probability formation. The consumer study also faces limitations related to hypothetical bias, informational overload in multi-attribute labels, and the potential endogeneity of environmental attitudes despite the implementation of a control-function approach. As with many stated preference studies, the observed preferences may not fully translate into real market behavior. Finally, the SEV framework depends on strong assumptions regarding discounting, market completeness, and functional relationships between ecological stocks and WTP. While analytically tractable, these assumptions may not reflect the full complexity of biodiversity markets or the heterogeneity of societal preferences.

Building on the limitations and findings of this dissertation, several avenues for future research emerge. First, expanding the meta-analytic framework to incorporate ecosystem condition indicators, spatially explicit variables, and service-specific value functions would greatly enhance the precision and policy relevance of value transfers. The increasing availability of geospatial datasets and machine-learning tools offers promising opportunities for developing such refinements. Second, further research is needed on the integration of behavioral complexity into agri-environmental policy design. This includes the modeling of learning under uncertainty, dynamic risk preferences, adaptation to climate-related shocks, and the role of peer effects in the adoption of sustainable practices. Combining experimental economics with longitudinal data would allow for more nuanced insights into the evolution of farmers' decision-making processes. Third, in consumer research, future studies should test ES-informed labeling strategies in real-market or experimental-auction settings, explore the

interaction between digital information technologies and sustainability labels, and assess the long-term behavioral effects of repeated exposure to ES-related claims. Fourth, methodological development of SEV approaches should focus on relaxing strong assumptions, testing alternative functional forms for stock-dependent preferences, and conducting extensive sensitivity analyses regarding discount rates, ecological trajectories, and transition dynamics. Integrating biophysical ecosystem models with economic valuation frameworks represents an especially promising direction for capturing non-linearities, thresholds, and irreversibilities in ecosystem dynamics. Finally, future research should aim to embed these methodological innovations within broader policy evaluation frameworks, examining how SEEA-aligned valuation metrics can inform risk assessments, regulatory design, green budgeting, and the monitoring of nature-related financial disclosures.

In conclusion, this thesis contributes to the ongoing transformation of economic measurement and policy design in the face of biodiversity loss and environmental degradation. By integrating ES valuation, behavioral analysis, and accounting principles within a coherent framework, it provides both conceptual clarity and operational tools to support more sustainable agri-food systems. In doing so, it responds to the growing demand from policymakers, statisticians, and financial institutions for rigorous, decision-relevant evidence on the value of nature, and it advances the broader objective of aligning economic systems with the biophysical foundations upon which they ultimately depend.

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