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Public preferences for energy sources in Italy

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ABSTRACT

National Energy and Climate Plans (NECPs) are the primary roadmaps for European Union countries to achieve their 2030 targets for energy and climate, guiding investment decisions and a significant economic transformation. We conduct a discrete choice experiment to analyze preferences for different energy sources in Italy. We examine preferences regarding various attributes: the capacity shares of the most significant current and projected energy sources, the reliability of the supply of electricity, and cost. We use a latent class model to estimate the willingness to pay (WTP) for each attribute, finding that these preferences can be categorized into four groups. On average, we find overall support for the major renewable energy sources, opposition to fossil fuels and service interruptions, and strong opposition to nuclear power. Based on these results, we calculate the consumer surplus associated with the implementation of the national plan. The results show that the WTP aggregated over Italian households is lower than the investment levels estimated in the NECP. Spreading out the investments envisaged in the NECP over time can bring costs and benefits into better balance.

1. Introduction

Climate change has become one of the most pressing challenges of the 21st century, threatening economic, social, and environmental stability on a global scale. Decarbonizing the electricity sector is one of the essential strategies to mitigate greenhouse gas (GHG) emissions and fulfill the objectives established in the Paris Agreement (UNFCCC, 2015). In Europe, the transition to renewable energy sources (RES) is not only an environmental priority but also a political and economic imperative (Council of the European Union, 2022). However, this transition will require massive investments, the financial and social implications of which are the subject of intense debate (ARERA, 2024; Compagnucci and Spigarelli, 2023).

National Energy and Climate Plans (NECPs) are pivotal for achieving Europe's ambitious decarbonization goals (MIMIT, 2019). Their importance lies in providing a consistent, transparent, and coherent framework for all countries in the EU through an integrated plan. These plans require each country to outline concrete policies and measures for a ten-year period, with intermediate updates (currently 2021–2030), regarding key dimensions, including reductions in GHG, deployment of renewable energy, energy efficiency, and energy security. This integrated plan ensures coordinated action and promotes collective progress toward the EU's climate goals. In addition, it guides national policymaking and enables the European Commission to monitor progress and assess whether the collective level of ambition is sufficient, or, in contrast, the updating of different targets will be necessary (MASE, 2024).

Meeting the ambitious decarbonization and energy transition goals outlined in these plans requires profound transformations in multiple sectors, demanding substantial national investments, particularly as the capital needed for initiatives like deploying a renewable energy infrastructure and modernizing grids constitutes a significant financial undertaking for each country (European Commission, 2024). In this context, it is crucial to understand whether society's preferences and willingness to pay (WTP) for different energy sources are aligned with the investments needed for this decarbonization. How does society perceive the balance between long-term environmental and economic benefits, as set out in the roadmap developed by European regulators, and short-term economic sacrifices? Moreover, public support is unlikely to be homogeneous: different population groups may value energy technologies and policy trade-offs in distinct ways. Capturing this heterogeneity is fundamental to the design of effective and sustainable policies that can garner broad and durable social acceptance.

This study contributes to the debate with several novel elements. First, it provides new and comprehensive discrete choice experiment (DCE) evidence on preferences for Italy's electricity mix, covering a

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broad set of current and prospective technologies expressed as changes in relative capacity shares, an intuitive format for eliciting preferences over national energy portfolios that remains uncommon in the stated-preference literature. Second, we quantify household WTP for the specific 2030 electricity-mix pathway proposed in Italy's 2023 NECP, enabling a direct comparison between elicited welfare gains and the magnitude of planned investments, an explicit link that is still seldom made in valuation studies concerned with electricity mixes. Third, we examine preferences regarding a hypothetical reintroduction of nuclear power, providing timely evidence for a country where nuclear policy has been politically sensitive for decades and where recent empirical preference estimates are limited. Fourth, we model preference heterogeneity using a latent class model (LCM), which captures markedly different preference patterns toward fossil fuels, renewables, nuclear power, and supply reliability across population segments. By relating class membership to socio-demographic characteristics, we show how support for alternative pathways, including the 2030 scenario, varies across groups, yielding insights relevant for targeted and socially feasible policy design. Taken together, these features position our analysis to inform national policy in Italy and contribute to comparative research on energy transitions across the EU.

This study focuses on Italy, whose power sector is the third-largest contributor to CO2 emissions in the EU (Crippa et al., 2024). In our DCE, alternatives are defined by three attribute groups: changes in technology-specific installed-capacity shares (percentage points), changes in annual outage duration (minutes/year), and a bill surcharge (€/bi-monthly). These attributes were selected to mirror the main levers in national electricity planning (mix, reliability, and cost). The experiment covers the major current and prospective technologies and presents capacity changes in percentage terms, which enhances respondent comprehension and improves the accuracy of elicited preferences. We also analyze WTP for reductions in the total duration of power outages and for a hypothetical reintroduction of nuclear energy. The LCM reveals four distinct classes of respondents, with socio-demographic variables predicting the probability of class membership. We estimate the class-specific WTP for each attribute and compute the consumer surplus associated with the 2030 scenario.

The aggregated WTP estimates show that the consumer surplus associated with the 2030 scenario, relative to the status quo (SQ), is significantly below the investment levels required by the Italian NECP. This does not imply societal resistance to transforming the energy system. On the contrary, we find strong support for renewable technologies. However, it suggests that spreading the planned investments over a longer time horizon may better balance perceived costs and benefits. Our findings thus provide valuable insights for Italian policymakers responsible for implementing the NECP. For decision-makers in other countries, this work underscores the need to complement investment plans with cost–benefit analyses grounded in heterogeneous household preferences. Given the rapid technological and political evolution of the energy sector, updated evidence on public preferences remains essential to guide future policy decisions.

This paper is structured as follows: Section 2 presents a literature review and the current and projected composition of the Italian electricity mix. Section 3 presents the experimental setup and the econometric model. Section 4 presents the results of the DCE. Section 5 discusses the results and the policy implications of our findings and concludes.

2. Literature review and the Italian energy context

2.1. Related literature

We structure this review around (i) how preferences for electricity attributes are elicited and how heterogeneity in those preferences is addressed, (ii) evidence on energy-technology preferences in Italy, and (iii) studies comparing aggregate WTP with the costs of meeting national policy targets, to clarify how prior findings inform our design and analysis.

2.1.1. Eliciting preferences for electricity sources and modeling heterogeneity

Several studies have examined individuals' WTP for different electricity sources, with a particular focus on renewable energy, in various countries. For example, Murakami et al. (2015) explore the WTP of consumers for nuclear and renewable electricity in Japan and the United States. For South Korea, Huh et al. (2015) use a DCE to analyze preferences for improved residential electricity services considering attributes such as increases in RES or reductions in the cumulative annual duration of blackouts, and Kim et al. (2018) investigate the public acceptance of different energy sources. For Australia, Borriello et al. (2021) employ a DCE and a latent class hybrid choice model to estimate individual WTPs for four renewable and four non-renewable energy sources. Similarly, Tocock et al. (2023) conduct a DCE to analyze the preferences of Australian households for alternative electricity contracts, including features that reflect potential future energy policy changes, and estimate the WTP for these attributes. This strand of work motivates our use of a DCE to quantify trade-offs across technologies and service reliability in WTP terms. It also suggests that average WTP estimates can mask substantial differences across respondents, which reinforces the importance of modeling heterogeneity explicitly.

Beyond single-country studies, broader reviews and meta-analyses provide further insights into consumer preferences for renewable energy. Hwang et al. (2024) present a comprehensive review of the literature on the choice experiments used to estimate WTP. Wang et al. (2024) and Chaikumbung (2021) apply meta-regression techniques to synthesize the empirical findings for multiple countries, identifying key factors that influence consumers' WTP. A global meta-analysis by Cerdá et al. (2024) estimates that the average household's WTP for renewable energy falls between €113 and €124 per year, with regional variations showing higher values in southern Europe and lower values in Asia. The wide variation in reported WTP across settings also highlights the limits of relying on average WTP estimates alone, a point we address in our application using a latent class specification.

2.1.2. Public preferences for energy technologies in Italy

Italian studies have also used DCEs to analyze preferences regarding electricity sources. For instance, Cicia et al. (2012) present a DCE using stated preference (SP) data and an LCM to quantify preferences for the origin of the electricity supplied to the household. They conclude that in 2009, 35% of the Italian population had a strong preference for wind and solar energy and disliked both biomass and nuclear energy; 33% had a moderate preference for solar and wind energy and disliked both nuclear power and biomass; and the remaining 32% had a strong preference for solar, wind, and biomass, while being strongly opposed to nuclear energy. Building on this Italian evidence, our study contributes by eliciting portfolio-level preferences using changes in national capacity shares (percentage points), a representation that aligns closely with how NECP targets are formulated.

Both Vecchiato (2014) and Vecchiato and Tempesta (2015) employ a DCE to analyze preferences for renewable energy in Italy, with a shared focus on WTP and the importance of landscape preservation. In particular, Vecchiato (2014) examines attitudes toward wind farms, finding a preference for offshore wind farms due to concerns about landscape aesthetics, while Vecchiato and Tempesta (2015) investigate consumers' preferences for electricity contracts featuring different renewable energy sources. Both studies highlight a generally positive perception of renewable energy and emphasize that proximity to residential areas plays a crucial role in shaping public acceptance, with respondents favoring energy infrastructure located at a minimum distance from homes. This finding is a classic example of the well-known Not In My Back Yard (NIMBY) effect regarding wind energy development (van der Horst, 2007). More recently, Vergine et al. (2024) investigate community acceptance of a proposed offshore wind farm in Southern Italy, finding that place attachment and increasing concern about climate change also shape support. Because our focus is national portfolio planning rather than local siting, we do not include landscape or proximity attributes; instead, we capture national-level trade-offs through technology shares, outage duration, and cost, incorporating nuclear power as a salient, policy-relevant attribute in the Italian context.

Alberini et al. (2018a,b) explore public preferences for climate change mitigation policies, focusing on the reduction of CO2 emissions. Using DCEs, they find substantial heterogeneity in WTP, influenced by factors such as income and the design of the policy. Alberini et al. (2018a) compare Italian and Czech households, while Alberini et al. (2018b) extend the analysis to examine the role of individual characteristics and policy instruments, revealing significant variations in WTP. In a related domain, Contu and Strazzera (2022) investigate preferences for nuclear energy in Italy, incorporating a discrete choice model that takes into account heterogeneity in decision-making processes and the influence of salient attributes. Their findings highlight the importance of cognitive heuristics in shaping choices and suggest that traditional models may overestimate the WTP compared to approaches considering saliency effects. These Italian findings directly inform our attribute selection (including nuclear and reliability) and motivate our use of an LCM to capture heterogeneity.

2.1.3. Aligning aggregate willingness to pay with national policy costs

Different SP studies have been used to analyze both the WTP of Italian households for green electricity and the discrepancy between the total WTP of the population and the costs required at the national level to meet the targets set by the government for renewable capacity. For example, Bollino (2009) presents an SP study that analyzes the WTP for renewable energy in Italy using different methods of estimation and compares the aggregate WTP of the population with the amount needed to meet the Italian government's installation target at the time. He concludes that the estimated WTP of Italian households was insufficient to cover the costs necessary to achieve the target set by the government at the time (an additional 19,130 GWh to be produced by RES in 2010). Similarly, Bigerna and Polinori (2014) use a nationwide household survey conducted in Italy in November 2007 and, using different models, conclude that the median WTP for green electricity is between €4.62 and €8.05 every two months per household, meaning that the total estimated WTP of the population accounted for only between 8.6% and 15.1% of the cost of achieving the corresponding national target. These studies motivate our comparison between the aggregate welfare implied by household preferences and the investment needs in the updated NECP.

Despite these contributions, important gaps remain. First, existing Italian DCE evidence often focuses on specific technologies (e.g., wind or solar), localized projects, or generic "green electricity", whereas evidence for preferences over a full national electricity mix expressed in relative shares remains limited. This metric is important for consistency with policy planning, which is typically formulated in percentage terms (e.g., shares of renewables, fossil fuels, or nuclear). Second, prior Italian studies generally do not compute WTP for the specific 2030 electricity mix defined in the updated NECP, nor do they assess the alignment between population-level WTP and national investment requirements. Third, while some studies analyze nuclear attitudes, few examine nuclear reintroduction alongside a comprehensive portfolio of renewables and supply-reliability attributes within a single unified framework. Our study addresses these gaps by implementing a DCE that mirrors the structure of the updated NECP and enables a direct comparison between societal preferences and planned energy-system investments, while accounting for preference heterogeneity via an LCM.

2.2. Italy's electricity mix: Current situation and future prospects

To clarify the role of the Italian energy context in our empirical analysis, this section provides the inputs used in three stages of the paper. First, the most recent installed-capacity shares define the SQ electricity mix displayed in the DCE choice cards. Second, reliability indicators motivate and calibrate the "Outages" attribute and its SQ level. Third, the 2030 targets in the 2023 NECP define the policy counterfactual used to compute the welfare change (change in consumer surplus/compensating variation) relative to the SQ, while the NECP investment figures provide the benchmark against which we compare the aggregate welfare estimates.

The energy industry in Italy (the production of electricity and heat, plus oil refining) is the principal contributor to national GHG emissions, with a share in 2022 of about 23%. Since 2005, GHG emissions coming from this industry have decreased by approximately 41% (ISPRA, 2024). This gradual reduction is partly due to changes in Italy's electricity mix, driven by the increasing use of RES. However, natural gas remains the primary source of electricity. For instance, the share of fossil fuels in the gross generation of electricity in 2023 was 55.5%, with natural gas alone accounting for 45% (ARERA, 2024). Fig. 1 shows the evolution of installed renewable capacity in Italy from 2000 to 2023 (Terna, 2024). Total thermoelectric capacity, including both cogeneration and non-cogeneration plants (natural gas, oil products, coal, etc.), is represented by the dashed line. As can be seen, the renewable sources with the highest growth are solar and wind, increasing from 0.0 GW and 0.3 GW in 2000 to 30.3 GW and 12.3 GW in 2023, respectively. Thermoelectric capacity was almost triple that of renewable capacity in the early 2000s. It was not until 2023 that RES capacity exceeded thermoelectric capacity for the first time.

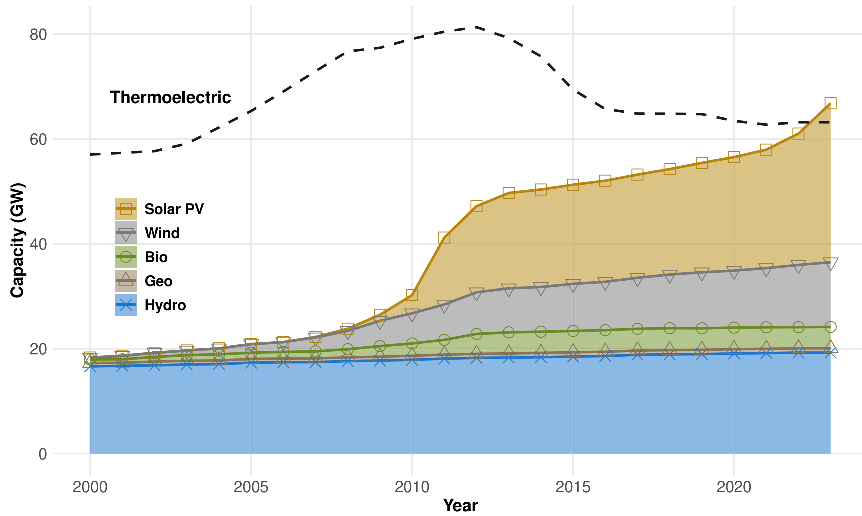
The 2019 NECP set sectoral and global energy targets for 2021–2030. Some of these targets exceed the mandatory levels set by the EU.[1] The new 2023 NECP modified the previous plan by agreeing on targets for 2030 based on a more realistic and technologically neutral approach and the new context. According to the new plan, Italy's electricity mix should be transformed by 2030, with a leading role for renewables, the phasing out of coal, and a significant reduction in the use of fossil fuels. By the end of 2022, Italy's electricity mix included 7.3 GW of coal plus oil, 44.0 GW of gas, 19.3 GW of hydro, 11.9 GW of wind, 25.1 GW of solar, 0.8 GW of geothermal, and 4.0 GW of bioenergy (Terna, 2023).

To meet the updated targets, Italy needs to achieve a capacity of 131 GW from renewable sources by 2030. Nearly 79.3 GW of this should come from solar, 28.1 GW from wind, 19.4 GW from hydro, 3.2 GW from bioenergy, and 1 GW from geothermal (MASE, 2024). At the same time, coal-fired power plants are to be phased out, while gas-fired capacity remains unchanged.

The 2023 NECP does not envisage the reintroduction of nuclear power by 2030 but does include the possibility of its reintroduction into the energy mix by 2050, expecting it to cover 11% of the total demand for electricity by 2050, with a possible projection of 22%. Although nuclear power was phased out in Italy in 1990, Italy imports nuclear energy from neighboring countries, notably France and Switzerland. However, the possibility of new nuclear power plants being built in Italy is unlikely in the short term due to widespread political opposition to nuclear power. For instance, Bersano et al. (2020) review the history of nuclear power in Italy and discuss the advantages and disadvantages of its hypothetical reintroduction. They conclude that the main disadvantages of its reintroduction concern public opposition and the management of nuclear waste.

Achieving the national targets will require billions of euros of public and private investment until 2030 (Esposito and Romagnoli, 2023). According to the 2023 NECP, the needed cumulative investments in new renewable capacity for solar PV and wind power will be approximately 80 billion euros during 2024–2030, in contrast to the 2 billion euros expected for fossil capacity. In addition, cumulative investment in the development of the national transmission grid and the upgrading of distribution grids, a requirement for the electricity system to accommodate more renewables being connected to the grid, is expected to be 30 billion euros (MASE, 2024).

[1] See Appendix A for a summary of the most relevant energy policy initiatives, both at the national and international levels, concerning the deployment of RES in Italy in recent years.



* Own elaboration with data from the Italian TSO (Terna, 2024).
** Bio refers to bioenergy for dual purposes (heat+electricity).

Fig. 1. Evolution of gross RES capacity in Italy.

3. Methodology

3.1. Survey design and experimental setup

The study is based on an online survey administered in Italy in March 2024. Respondents were recruited through a survey company using one of its online panels. Before launching the main survey, the questionnaire was pre-tested through focus groups and a pilot study. The target sample size was set ex ante at approximately 800 completed questionnaires, based on methodological recommendations for discrete choice experiments and a simulation-based assessment under a baseline logit specification (Mariel et al., 2025). Because the sample is not a simple random sample or a probability-based stratified sample, design-based margins of error for population proportions are not reported. Statistical uncertainty for the model estimates and welfare measures is instead quantified using model-based confidence intervals derived from the robust asymptotic variance of the estimator.

The survey has three sections. The initial section gives the respondents an introduction to the questionnaire and collects basic socio-demographic information. The second one is the DCE. The final part of the survey asks a series of attitudinal and attribute non-attendance questions (ANA).

The DCE presents respondents with three distinct scenarios for the composition of the Italian electricity mix: two alternatives with different levels of the different attributes, and the SQ option. The initial set of attributes and their levels was pre-defined based on technically and policy-plausible values anchored to Italy's electricity mix and consistent with the NECP context. The focus groups involved twelve participants of diverse backgrounds and were used to assess respondent comprehension and refine the presentation of the choice tasks. In addition, a pilot study with 240 participants was conducted to ensure that the survey instrument and the choice tasks were understandable. Table 1 presents the definitions of these attributes and their corresponding levels.

The final set of attributes covers three different dimensions: (i) the change in the share of installed capacity of the sources of electricity that are considered (expressed in percentage points), namely coal & oil, gas, nuclear, hydroelectric, wind, solar, geothermal, and biomass, (ii) the change in accumulated duration of power outages, expressed in minutes per year, and (iii) the change in the cost of the electricity bill (paid every two months) expressed in euros.[2] We selected these specific attributes because they represent the primary policy levers in the NECP framework. Because our objective is to elicit preferences at the macroeconomic and national portfolio level, we do not include location-specific or NIMBY-related attributes (e.g., turbine proximity or visual landscape impacts), which are better suited for project-level valuation.

A full factorial design with two varying alternatives and a non-varying SQ would involve $(5^9 \cdot 10)^2$, i.e., more than 381 trillion, different choice situations. In line with best practice in DCE design (Mariel et al., 2025), we generated a D-efficient experimental design for a multinomial logit (MNL) model consisting of one hundred rows from which the sequence of choice tasks assigned to each individual is randomly sampled. The design was generated by using the R library *spdesign* (Sandorf and Campbell, 2023). The final design converged to a D-error of 0.00286 under the priors used for design generation.

Note that there is an additional difficulty in generating the design of this particular DCE. As the levels represent changes from the SQ scenario, combinations resulting in large changes in total capacity are unrealistic. At the same time, combinations yielding the same total capacity as the SQ result in a non-identifiable model since the level of any energy source would necessarily be a linear combination of the levels of the remaining sources in the same alternative. Therefore, we decided to keep only those combinations that result in a cumulative deviation within the range of ±5 pp, as the excess (shortfall) of energy to meet demand can always be exported (imported).

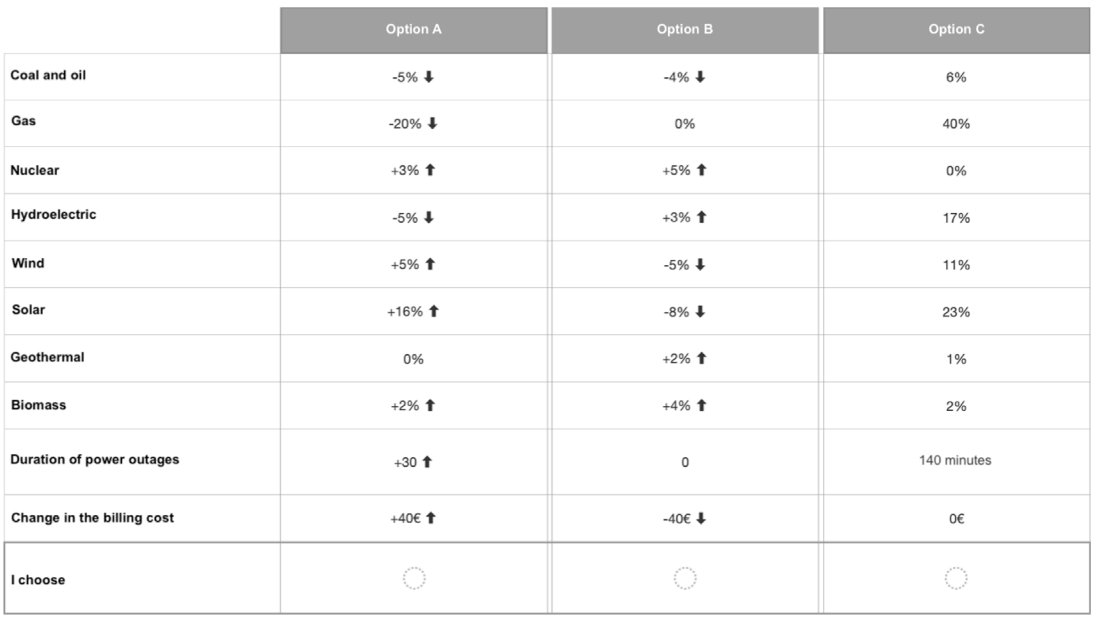
To facilitate the participants' comprehension, alternatives 1 and 2 in each choice card show the relative changes with respect to the SQ (expressed in percentage points) accompanied by arrows indicating the sign of the change. In contrast, the third column shows the actual SQ levels, not changes (i.e., they are all equivalent to a zero percentage point change). Each participant faces eight consecutive choice tasks. Fig. 2 shows an example of a choice card.

[2] Note that this representation of Italy's electricity mix is a broad approximation. The actual generation landscape is more nuanced and may include plants using multiple fuel sources or technologies, other minor energy sources not explicitly listed, and different sub-technologies within each broad category. This simplification aims to provide a general overview to the respondents.

Table 1
Attributes and levels.

Label	Definition	Levels
Coal	Change in installed coal and oil capacity (pp)	−6, −5, −4, −2, 0[a]
Gas	Change in installed gas capacity (pp)	−25, −20, −15, −10, 0[a]
Nuclear	Change in installed nuclear capacity (pp)	0[a], 3, 5, 7, 10
Hydro	Change in installed hydroelectric capacity (pp)	−5, −3, 0[a], 3, 5
Wind	Change in installed wind capacity (pp)	−5, 0[a], 5, 10, 15
Solar	Change in installed solar capacity (pp)	−8, 0[a], 8, 16, 24
Geo	Change in installed geothermal capacity (pp)	−1, 0[a], 2, 4, 6
Bio	Change in installed biomass capacity (pp)	−2, 0[a], 2, 4, 6
Outages	Change in accumulated duration of power outages (min/year)	−10, 0[a], 10, 20, 30
Surcharge	Change in the cost of electricity bills (€/bi-monthly)	−40, −30, −20, −10, 10, 20, 30, 40, 60, 80

Note:
[a] Levels represent the status quo scenario.



	Option A	Option B	Option C
Coal and oil	-5% ⬇	-4% ⬇	6%
Gas	-20% ⬇	0%	40%
Nuclear	+3% ⬆	+5% ⬆	0%
Hydroelectric	-5% ⬇	+3% ⬆	17%
Wind	+5% ⬆	-5% ⬇	11%
Solar	+16% ⬆	-8% ⬇	23%
Geothermal	0%	+2% ⬆	1%
Biomass	+2% ⬆	+4% ⬆	2%
Duration of power outages	+30 ⬆	0	140 minutes
Change in the billing cost	+40€ ⬆	-40€ ⬇	0€
I choose			

Fig. 2. Example of a choice card presented to the respondents (translated from the Italian).

The percentages of each technology in the SQ option resulted from the most recent data published by the Italian transmission system operator (TSO) before the survey was conducted (Terna, 2023).[3] The SQ's value for the accumulated duration of power outages, including those with and without prior notice, was taken from the Italian Regulatory Authority for Energy, Networks and Environment (ARERA, 2023). In addition, we included a budget and a consider-all reminder at the top of each choice card to minimize potential hypothetical bias. Specifically, the wording of these reminders was (here, translated from the Italian) "Compare the three options taking into account the values assigned to all attributes" and "Consider the increase in the electricity bill indicated in some options as money no longer available for other needs".

3.2. Econometric model

The random utility maximization (RUM) model is typically the basic theoretical framework for analyzing the data collected in DCEs. The baseline specification in the RUM framework is the MNL model, which assumes homogeneous preferences. However, the need to capture preference heterogeneity, observed and unobserved, often motivates using approaches like the LCM, which assumes Q latent classes (Greene and Hensher, 2003). It is important to note that the preference patterns reflected by the classes are not predetermined by the researcher. Although the researcher must inform the estimation procedure about the number of classes, the LCM estimates the classes endogenously through maximum likelihood, identifying groups of individuals who share similar preference parameters. Class membership is therefore probabilistic rather than deterministic. Each class q is characterized by different linear utilities with class-specific parameters:

$$U_{njt|q} = \mathrm{ASC}_{j|q} + \mathbf{x}'_{njt}\boldsymbol{\beta}_q + \varepsilon_{njt}, \tag{1}$$

where $\mathrm{ASC}_{j|q}$ is the alternative-specific constant (ASC) associated with alternative j, $\mathbf{x}_{njt}$ is the vector of attributes presented to individual n in alternative j at choice occasion t, and ε_{njt} are error terms. The ASC of one of the alternatives is usually set to zero for model identification. Under the assumption that the random terms ε_{njt} are i.i.d. extreme value type I with location parameter zero and scale parameter one, also known as Gumbel(0,1) type errors, the probability $p_{nit|q}$ that individual n selects alternative i at occasion t, conditional on membership in class q, is described by the following conditional logit structure (McFadden, 1974):

$$p_{nit|q} \equiv \mathbb{P}(U_{nit|q} > U_{njt|q},\ \forall j \neq i) = \frac{\exp(\mathrm{ASC}_{i|q} + \mathbf{x}'_{nit}\boldsymbol{\beta}_q)}{\sum_{\ell=1}^{J} \exp(\mathrm{ASC}_{\ell|q} + \mathbf{x}'_{n\ell t}\boldsymbol{\beta}_q)}. \tag{2}$$

As class membership is unobservable, individuals are not assigned to classes beforehand. Instead, the probability that individual n belongs to class q is estimated from the data, typically using a multinomial logit

[3] For bioenergy, we ignored the capacity for dual use (i.e., heat+electricity).

structure:

$$\pi_{nq} = \mathbb{P}(n \text{ belongs to class } q) = \frac{\exp(\varphi_q + \mathbf{z}'_n \boldsymbol{\gamma}_q)}{\sum_{c=1}^{Q} \exp(\varphi_c + \mathbf{z}'_n \boldsymbol{\gamma}_c)}, \tag{3}$$

where $\mathbf{z}_n$ is a vector of observable characteristics of individual n (typically socio-demographic variables), $\{\boldsymbol{\gamma}_q\}$ are the class-specific parameter vectors, and $\{\varphi_q\}$ are class-specific constants. The parameters φ and $\boldsymbol{\gamma}$ of one of the classes are usually set to zero for model identification.

The class conditional probability that an individual selects a particular sequence of alternatives over a series of choice tasks is the product of the class conditional probabilities in each choice occasion. Therefore, the overall probability that an individual selects a specific sequence of choices is the sum of the class conditional probabilities for the sequence of choices, weighted by the probability of belonging to each class. Using an indicator function y_{njt} to denote the choices made by individuals, where $y_{njt} = 1$ if individual n chooses alternative j at occasion t, but $y_{njt} = 0$ otherwise, the log-likelihood function can be expressed as

$$\log L = \sum_{n=1}^{N} \omega_n \log\left(\sum_{q=1}^{Q} \pi_{nq} \prod_{t=1}^{T} \prod_{j=1}^{J} p_{njt|q}^{y_{njt}} \right), \tag{4}$$

where the ω_n are individual-specific weights that adjust the influence of each observation when the sample does not closely reflect the population. This reweighting aims to improve representativeness by bringing the sample composition closer to observed population characteristics. Statistical inference is based on the robust asymptotic variance of the latent class estimator (Alcorta and Mariel, 2026).

For class q, the class-specific WTP for a non-monetary attribute (ℓ) is the negative of the ratio of the parameter associated with that attribute ($\beta_q^{(\ell)}$) to the parameter associated with the cost ($\beta_q^{(c)}$): $\text{WTP}_{\ell|q} = -\beta_q^{(\ell)}/\beta_q^{(c)}$. The estimated expected WTP of individual n for a particular non-monetary attribute ℓ, conditional on that individual's observed covariates, is then the weighted average of the class-specific WTP estimates, weighted by the estimated probabilities of belonging to each class:

$$\widehat{\text{WTP}}_{n\ell} = \sum_{q=1}^{Q} \hat{\pi}_{nq}\, \widehat{\text{WTP}}_{\ell|q} = \sum_{q=1}^{Q} \hat{\pi}_{nq} \left(-\frac{\hat{\beta}_q^{(\ell)}}{\hat{\beta}_q^{(c)}} \right). \tag{5}$$

It could be the case that researchers or policymakers are not primarily interested in estimates of the marginal WTP but rather in the overall monetary value that the population places on a given policy intervention. There are different welfare measures and different approaches typically used in DCEs for environmental valuation: compensating variation (CV), equivalent variation (EV), and the change in consumer surplus (ΔCS) (e.g., Hanemann, 1984; McConnell, 1995). When utilities are linear in all parameters, as in our case, CV = EV = ΔCS; see, for example, Varian (1992, Chapter 10) or Mas-Colell et al. (1995, Section 3.1). In this case, the common value of these measures represents the overall WTP of the individual for the bundle of changes due to the policy intervention rather than for some marginal changes in some attribute.

Therefore, we can directly estimate the value of these welfare measures for some policy intervention that modifies the levels of L attributes with respect to the SQ values. Let x_ℓ^{SQ} and x_ℓ^{N} be the SQ value and the new value of the ℓth attribute, respectively. The estimated ΔCS of individual n for this intervention is thus

$$\widehat{\Delta\text{CS}}_n = \sum_{\ell=1}^{L} (x_\ell^N - x_\ell^{SQ})\, \widehat{\text{WTP}}_{n\ell}. \tag{6}$$

Since the number of classes is not a parameter of the model, it is common practice to estimate the model with different numbers of classes. The determination of the appropriate number of classes is usually based on specific information criteria such as the AIC, AIC3, BIC, or CAIC. However, as highlighted by several authors, the researcher's judgment of the appropriateness of the model should also be considered (Hynes et al., 2008; Scarpa and Thiene, 2005).

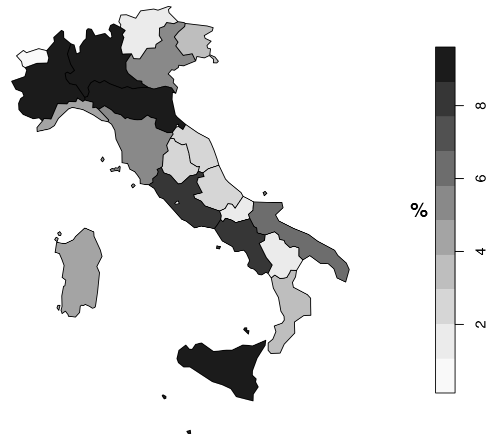


Fig. 3. Share of respondents in each region of Italy.

4. Results

The final sample consists of 812 respondents. As each respondent answered eight choice tasks, the total number of observations collected in the DCE was 6496. Table 2 shows the recorded values and their frequencies for the main socio-demographic variables in our sample. Fig. 3 shows the geographical representation of the number of respondents in each region of Italy. As can be seen, our sample contains observations for every region. However, as the number of sampled individuals per region does not accurately reflect the expected frequency for each region, we use region-specific post-stratification weights in all estimations. For each respondent in a given region, the weight is defined as the ratio between the population share and the sample share of that region, based on Italian population data from ISTAT (2024b). Since both quantities are expressed as shares, the weights are implicitly normalized to have mean one in the sample. These region-specific weights are reported in Appendix B (Table B.1). Because age and gender are explicitly included as determinants of class membership in the latent class model, while region is not, the main post-stratification adjustment focuses on the regional distribution.

Following the approach presented in Section 3.2, we represent the class conditional utilities of individual n at choice-occasion t for this 3-alternative model as in Eq. (1), where the vector of attributes is defined as $\mathbf{x}_{njt} \equiv (\text{Coal}_{njt}, \text{Gas}_{njt}, \text{Nuclear}_{njt}, \text{Hydro}_{njt}, \text{Wind}_{njt}, \text{Solar}_{njt}, \text{Geo}_{njt}, \text{Bio}_{njt}, \text{Outages}_{njt}, \text{Surcharge}_{njt})$, and $\text{ASC}_{1|q} \equiv 0$ for model identification.

We use a subset of the individual-level variables collected in the survey to define the probabilities of membership in each class. As socio-demographic variables, we include gender, an ordered age-group variable, and the square of the latter to allow for non-linear age dependencies in the allocation function. We also include a dummy variable to characterize individuals who choose not to report their income level: No-income = 1 if the respondent n does not report their income (11.1% of the individuals), and zero otherwise.

Our objective in defining the explanatory variables for the allocation function is to identify the largest possible subset of available individual characteristics that best capture the heterogeneity of preferences within the analyzed population. The socio-demographic variables education, number of children, geographical region, and household income were also explored in the class-allocation model. However, they did not yield statistically significant coefficients in any of the class-allocation equations and were therefore not retained in the final specification on grounds of parsimony and interpretability. Therefore, we define the vector of individual characteristics affecting the probabilities of belonging to one class or another as $\mathbf{z}_n \equiv (\text{Age}_n, \text{Age}_n^2, \text{Female}_n, \text{No-income}_n)$.

Table 2
Socio-demographic characteristics of the sample.

Age		Gender		Education		Income		Children	
Value (years)	%	*Value*	%	*Value*	%	*Value* (€)	%	*Value*	%
18–24	6.7	Male	60.3	Elementary	0.4	<1000	6.0	0	70.2
25–34	18.2	Female	39.7	Medium	7.4	1000–1500	13.4	1	19.2
35–44	22.9			Diploma	49.1	1501–2000	17.5	2	8.9
45–54	23.3			Bachelor's	16.0	2001–2500	14.9	3	1.2
55–64	17.7			Master's	24.8	2501–3000	12.6	4	0.2
65–74	9.7			PhD	2.3	3001–5000	17.6	5	0.0
75–84	1.1					5001–7000	3.2	6	0.1
≥85	0.4					>7000	3.7	7	0.0
						Not reported	11.1	8	0.0
								≥9	0.1

Note: Income refers to household income.

Table 3
Information criteria.

Variable	Number of classes			
	2	3	4	5
Parameters	29	46	63	80
Log-likelihood	−6041.5	−5787.1	−5683.6	−5632.5
AIC	12 140.9	11 666.2	11 493.3	**11 425.0**
AIC3	12 169.9	11 712.2	11 556.3	**11 505.0**
BIC	12 337.5	11 978.0	**11 920.4**	11 967.3
CAIC	12 366.5	12 024.0	**11 983.4**	12 047.3

Note: Bold values represent the minimum across classes.

We estimated the LCM with different numbers of classes using the *Apollo* software package (v0.3.5) developed by Hess and Palma (2019), implementing the BGW optimization algorithm (Bunch et al., 1993). Table 3 presents the values of the information criteria for the various models. Notably, both BIC and CAIC, which apply a stricter penalty for additional parameters than do AIC and AIC3, suggest a four-class model. In contrast, AIC and AIC3 suggest five classes. Since AIC and AIC3 often overestimate the number of classes, we follow BIC and CAIC and proceed with a four-class model.

Table 4 shows the estimates for the four-class model (where Class 1 is the reference class for the allocation function). As shown, the classes have estimated mean assignment probabilities, $\overline{\pi}_q \equiv N^{-1}\sum_{n=1}^{N}\pi_{nq}$, of 11.97%, 41.65%, 16.75%, and 29.63%, respectively. The probability of being in either Class 2 (the largest class) or Class 4 shows a quadratic pattern across age groups: it decreases up to the 55–64 age interval and then increases for older groups. The estimates also indicate that not reporting household income or being female decreases the chances of belonging to either Class 2 or Class 3.

From the estimates of the parameters, we obtain the class-specific WTP estimates for each non-monetary attribute as discussed in Section 3.2 and present them in Table 5. Standard errors of these class-specific WTP estimates are calculated using the delta method (e.g., Hayashi, 2000, Lemma 2.5) with the robust estimator of the variance.[4] Note that the WTPs for the power outages attribute have been rescaled for ease of interpretation (WTP values for a ten-minute increase in the duration of power outages). As shown in Tables 4 and 5, Class 1 strongly opposes nuclear power and has substantial estimated WTP for bioenergy. In contrast, Class 2 has estimated disutilities for fossil fuels, power outages, and bioenergy, but positive WTP for nuclear power. Regarding Class 3, the only significant attribute was the monetary one (see Table 4); this implies that the surcharge on the bill is the only attribute of importance to this class, while they are relatively indifferent to the other attributes. Lastly, Class 4 favors most RES, with significant WTP values estimated for hydro, solar, wind, and bioenergy, while not favoring nuclear power.

We then determined the expected WTP for each individual as in (5), i.e., the class-specific WTP estimates weighted by the estimated class-membership probabilities based on that individual's covariates. Fig. 4 shows the box plots of the distributions obtained. We observe higher estimated WTP for RES, especially for hydro and solar, which have mean values of 2.65 and 1.40 euros per percentage point increase in capacity, respectively. In contrast, fossil fuels (coal and gas) and especially nuclear power show distributions concentrated around negative values, i.e., disutilities, with mean values of −1.93, −0.51, and −3.69 euros per percentage point increase in capacity, respectively. The average estimated disutility for a ten-minute increase in the cumulative duration of annual blackouts is −3.30 euros, i.e., a WTP of 3.30 euros for a ten-minute decrease.

We can see in Fig. 4 that the dispersion of the estimated distributions varies from attribute to attribute. For example, we observe that the dispersion for nuclear power is considerably higher than for the remaining attributes, indicating much more heterogeneous preferences. Also, the estimates for bioenergy are more dispersed than for the major renewable technologies, i.e., hydro, solar, and wind. Finally, we observe that the interquartile range for the geothermal attribute includes zero, indicating substantial heterogeneity and no clear descriptive tendency toward either positive or negative WTP for this source.

Then, we estimated the change in consumer surplus associated with the change in the electricity mix proposed by the Italian government with a horizon of 2030. As discussed in Section 2.2, according to the latest national plans outlined in the 2023 NECP, the country needs to make profound changes in its electricity mix. The quantities used are shown in Table 6. Data for the SQ comes from Terna (2023), while data for the projected scenario for 2030 comes from MASE (2024). Since the DCE attributes are defined in terms of capacity shares, the welfare calculation is based on the implied change in the percentage composition of installed capacity between the SQ and the 2030 scenario. In this policy counterfactual, the outage attribute is held at its SQ level, since the NECP does not specify a directly comparable target for outage duration.[5]

Table 7 shows selected percentiles of the distribution of $\widehat{\Delta \mathrm{CS}}_n$ for the change in the scenario presented in Table 6, together with the mean value.[6] We observe that the distribution is left-skewed: the mean

[4] In what follows, when interpreting DCE results, we use "support"/"preference" to refer to positive WTP estimates and "opposition"/"disutility" to describe negative WTP estimates; these terms refer to choice-based welfare measures and are not intended as direct measures of attitudinal acceptance.

[5] The plan targets phasing out coal power plants, so we take this projected capacity to be zero. In contrast, it does not explicitly detail any reduction in gas capacity, so we assume this quantity to be static. The NECP sets the target for total bioenergy capacity (heat+electricity), so to be consistent with our DCE, we approximate this quantity by keeping the share of capacity for electricity generation only.

[6] As defined in (6), $\widehat{\Delta \mathrm{CS}}_n$ should be interpreted as an estimate of the expected consumer surplus for respondent n, conditional on that respondent's covariates.

Table 4
Estimation results.

Variables	Class 1		Class 2		Class 3		Class 4	
	Coef.	Std Err.	Coef.	Std Err.	Coef.	Std Err.	Coef.	Std Err.
ASC_2	−0.020	0.281	0.083	0.068	−0.158	0.193	0.349	0.105***
ASC_3	0.349	0.417	−1.989	0.244***	−0.450	0.329	−0.010	0.178
Attributes (β_q)								
Coal	−0.025	0.060	−0.060	0.018***	−0.048	0.065	0.036	0.023
Gas	0.038	0.033	−0.032	0.008***	0.034	0.038	0.017	0.012
Nuclear	−0.446	0.082***	0.019	0.010*	0.024	0.026	−0.026	0.014*
Hydro	0.063	0.043	0.006	0.012	0.026	0.036	0.057	0.017***
Wind	0.020	0.031	−0.008	0.007	0.035	0.026	0.027	0.010***
Solar	0.047	0.036	−0.006	0.008	0.036	0.034	0.037	0.012***
Geo	0.074	0.058	−0.005	0.015	−0.011	0.042	−0.009	0.019
Bio	0.120	0.067*	−0.043	0.016***	0.063	0.061	0.056	0.022**
Outages	0.001	0.010	−0.007	0.002***	−0.007	0.009	0.000	0.003
Surcharge	−0.014	0.004***	−0.009	0.001***	−0.079	0.012***	−0.009	0.002***
Class allocation (γ_q)								
Constant			4.63	1.518***	1.451	1.782	6.627	1.434***
Age			−1.112	0.593*	−0.221	0.748	−2.021	0.585***
Age^2			0.098	0.057*	0.015	0.076	0.168	0.058***
No-Income			−0.727	0.388*	−0.805	0.464*	−0.454	0.428
Female			−0.845	0.274***	−0.694	0.341**	−0.498	0.305
Mean class probability ($\bar{\pi}_q$)	11.97%		41.65%		16.75%		29.63%	

Robust (sandwich) standard errors are reported (White, 1982).
* Indicate the 10% significance level.
** Indicate the 5% significance level.
*** Indicate the 1% significance level.

Table 5
Class-specific WTP estimates (€).

Attributes	Class 1		Class 2		Class 3		Class 4	
	Coef.	Std Err.	Coef.	Std Err.	Coef.	Std Err.	Coef.	Std Err.
Coal (pp)	−1.815	4.442	−6.604	2.030***	−0.610	0.785	3.851	2.567
Gas (pp)	2.732	2.009	−3.504	1.008***	0.435	0.508	1.851	1.157
Nuclear (pp)	−31.786	10.970***	2.120	1.129*	0.303	0.334	−2.760	1.715
Hydro (pp)	4.500	3.090	0.612	1.345	0.323	0.487	6.074	2.157***
Wind (pp)	1.391	2.093	−0.856	0.807	0.444	0.354	2.861	1.056***
Solar (pp)	3.356	2.260	−0.618	0.918	0.456	0.460	3.995	1.301***
Geo (pp)	5.292	3.798	−0.518	1.699	−0.137	0.525	−0.951	2.063
Bio (pp)	8.535	3.885**	−4.722	1.950**	0.800	0.791	6.004	2.086***
Outages (10 min)	0.862	7.008	−7.492	2.262***	−0.872	1.135	−0.470	3.320

Standard errors are computed using the delta method with the robust estimator of the variance.
* Indicate the 10% significance level.
** Indicate the 5% significance level.
*** Indicate the 1% significance level.

Table 6
Capacities in the analyzed case.

Attribute	Capacity (GW)		Capacity (%)	
	SQ	2030	SQ	2030
Coal	7.3	0.0	6.6	0.0
Gas	44.0	44.0	39.9	25.4
Nuclear	0.0	0.0	0.0	0.0
Hydro	19.3	19.4	17.5	11.2
Wind	11.9	28.1	10.8	16.2
Solar	25.1	79.3	22.8	45.7
Geo	0.8	1.0	0.7	0.6
Bio	1.9	1.5	1.7	0.9
Total	110.2	173.3	100.0	100.0

value, $\overline{\Delta CS} \equiv N^{-1}\sum_{n=1}^{N}\widehat{\Delta CS}_n$, is 38.99, the median is 39.64, and the minimum and maximum values are 26.84 and 46.77, respectively. The standard error for $\overline{\Delta CS}$, calculated using the delta method with the robust estimator of the variance, is $SE(\overline{\Delta CS}) = 9.69$, which yields a 95% confidence interval of [20.00, 57.99].

Table 7
Summary of the distribution of $\widehat{\Delta CS}_n$ (€).

Statistic	Mean	P_0	P_5	P_{25}	P_{50}	P_{75}	P_{95}	P_{100}
Value	38.99	26.84	32.61	36.24	39.64	42.08	44.66	46.77

Given that aggregate welfare measures may be sensitive to sample composition, we also assess the robustness of the estimated mean change in consumer surplus to alternative post-estimation weighting adjustments. Let $\omega_n^{(m)}$ denote a set of weights associated with margin $m \in \{\text{region, age, gender}\}$, defined for each respondent as the ratio between the population share and the sample share of the respondent's category in that margin. For each weighting scheme m, we compute the weighted mean welfare measure as $\overline{\Delta CS}^{(m)} \equiv W_m^{-1}\sum_{n=1}^{N}\omega_n^{(m)}\widehat{\Delta CS}_n$, where $W_m \equiv \sum_{n=1}^{N}\omega_n^{(m)}$.

We use separate marginal adjustments rather than a full joint reweighting because finer cross-classifications would generate very sparse cells in our sample, and some joint population cells are not represented in the sample and therefore cannot be recovered by reweighting alone. For our purposes, marginal adjustments provide an informative robustness check, as they test whether the main welfare conclusion

Table 8
Sensitivity of the estimated consumer surplus to alternative marginal weighting schemes.

Weighting scheme	$\overline{\Delta CS}^{(m)}$ (€)	95% CI	Annual aggregate (billion €)	95% CI
Sample estimate	38.99	[20.00, 57.99]	6.08	[3.12, 9.05]
Region margin	39.01	[20.02, 57.99]	6.09	[3.12, 9.05]
Age margin	39.96	[20.60, 59.32]	6.23	[3.21, 9.25]
Gender margin	38.25	[19.13, 57.38]	5.97	[2.98, 8.95]

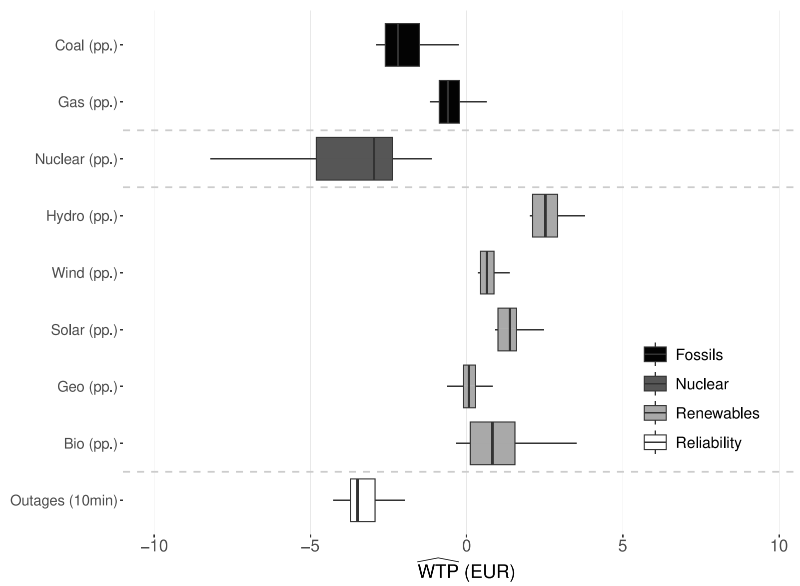


Fig. 4. Distribution of the WTP estimates.

is materially affected by aligning the sample with the key population margins.

Table 8 reports alternative post-estimation aggregations of the individual consumer-surplus predictions obtained from the main estimated model. The main model is estimated using region-specific weights. The first row ('Sample estimate') reports the simple unweighted mean of the predicted individual consumer-surplus values, while the remaining rows apply additional post-estimation marginal weights based on region, age, and gender, respectively. The alternative weighting schemes produce remarkably similar point estimates and confidence intervals for $\overline{\Delta CS}^{(m)}$, indicating that the aggregate welfare measure is highly stable to these adjustments in sample composition. Since the estimated consumer surplus is expressed at the household level on a bi-monthly billing basis, and Italy has approximately 26 million households (ISTAT, 2024a), the implied aggregate annual willingness to pay remains in a narrow range, between €5.97 and €6.23 billion depending on the weighting scheme. This strengthens our main result: even after aligning the sample separately with the population margins for region, age, and gender, the aggregate welfare implied by households' preferences remains well below the investment levels envisioned in the NECP.

5. Discussion and conclusion

In our DCE, the LCM identifies four preference classes. The largest (Class 2) rejects fossil fuels, bioenergy, and service interruptions while supporting nuclear power; the second-largest (Class 4) supports the major renewable technologies and opposes nuclear energy; the third-largest (Class 3) is virtually indifferent to all non-monetary attributes, being driven only by the cost of the electricity bill; and the smallest (Class 1) strongly dislikes nuclear power and favors bioenergy.

From a policy perspective, this segmentation shows which levers are most likely to generate support or resistance to NECP implementation across the population, insights that would be averaged out and harder to interpret in a single-class model. For instance, while Class 4 indicates support for the renewable-capacity targets outlined in the NECP, the existence of Class 3 suggests that, for a distinct segment of the population, support will be highly sensitive to the immediate financial burden (the bill surcharge) rather than to the technology mix itself. Furthermore, the strong aversion to power outages in Class 2 underscores that grid reliability must be prioritized alongside decarbonization to maintain public support. On average, respondents show a strong aversion to a hypothetical reintroduction of nuclear power in Italy and reject fossil fuels and service interruptions. In contrast, we find positive overall WTP estimates for most renewables, namely hydropower, solar PV, wind, and bioenergy.

The strong overall opposition to nuclear power is not unexpected, as Italy abandoned its nuclear power program following the 1987 referendum, heavily influenced by the previous year's accident at Chernobyl. This referendum resulted in the shutdown of all nuclear plants. Then, in 2011, shortly after the Fukushima disaster, a second referendum confirmed the strong public opposition to the revival of nuclear power in Italy, effectively confirming the country's no-nuclear stance. This finding is also consistent with results for other countries, e.g., Murakami et al. (2015) show that in both Japan and the US, there is a negative preference for increasing the share of nuclear power in the fuel mix (especially in Japan). In contrast, renewable energy sources were supported by both US and Japanese consumers, who show a willingness to pay $0.71 and $0.31 per month for a 1% increase in renewable energy sources. We also find a considerable aversion to fossil fuels, especially coal. This result is not surprising as coal is more polluting than gas (Zeng et al., 2022).

Overall, respondents value hydroelectric power the most, perhaps because they are familiar with it, as it is a very mature technology. As hydropower is more concentrated in fewer facilities, it is reasonable to assume that most respondents do not encounter hydroelectric dams regularly but do encounter more sparse technologies such as wind or solar, and are therefore less concerned about potential environmental or aesthetic impacts from this source. Further, Klinglmair et al. (2015) find that in Austria, a neighboring country whose main source of electricity is hydropower, most participants in a nationwide DCE on preferences for increasing hydropower capacity had a very positive attitude toward the construction of new hydropower plants, with only a minority opposed. However, they found that respondents preferred these new plants to be built away from their homes, i.e., the NIMBY effect. In contrast, Mattmann et al. (2016) find negative effects of hydropower due to the impact on the landscape.

The finding of significant disutilities for an increase in power outages is consistent with the extensive evidence that the reliability of the supply of energy is an essential attribute for consumers. Abrate et al. (2016) show that the typical Italian household would require compensation for even very short interruptions (1 min), ranging from €0.13 to more than €4.5. Empirical studies in other countries also find that the perceived costs of blackouts are high and that users are willing to pay to avoid blackouts or to minimize their duration and frequency, e.g., Reichl et al. (2013) for Austria, Ozbafli and Jenkins (2015) for Cyprus, and Huh et al. (2015) for South Korea.

Our results show that respondents prefer solar over wind, which could be for several reasons. Firstly, solar has low visual and noise impact, as it can be easily integrated into roofs or other infrastructure without much notice. Wind turbines, in contrast, can disrupt the landscape, emit disturbing noises, and endanger some bird species. It is well-known that wind projects suffer from the NIMBY effect (Olsen, 2010). For instance, Vecchiato (2014) shows that Italian households find that wind energy hurts the landscape and prefer wind turbines installed far from reachable viewpoints. Indeed, without further distinction, some respondents may associate solar energy with rooftop solar panels, which tend to be more widely accepted than both industrial-scale solar installations and wind farms, as subsidies and promotional campaigns have promoted solar energy in particular, reinforcing the perception that it is the most advantageous renewable option for both consumers and the environment (Cousse, 2021). Similar results arise in other studies. For example, in Italy, Vecchiato and Tempesta (2015) find that Italian households' WTP for photovoltaic is 3.4 times that for forest biomass and 5.4 times that for agricultural biomass. In line with our findings for Italy, Oehlmann and Meyerhoff (2017) and Bartczak et al. (2021) show that German and Polish residents prefer solar to wind to biomass, respectively.

We find that preferences for bioenergy are more heterogeneous in our data than for other renewables. A plausible explanation is that public familiarity with bioenergy varies widely across respondents. On the one hand, with less familiarity, willingness to pay may be positive due to the recognition as renewables but not as high as for widely publicized technologies such as solar or wind, or even close to zero, i.e., indifference on average. While solar or wind energy are associated with more immediate and easily understood images, bioenergy encompasses processes for obtaining and using biomass from energy crops to agroforestry residues whose complexity can lead to misunderstanding or ignorance. On the other hand, biomass has certain drawbacks that other renewable energy options do not, such as increased local truck traffic (with its associated pollution and disruption) and gaseous emissions from the plant, including unpleasant odors (Upham and Shackley, 2007). In addition, there is confusion about the actual impact on CO2 emissions. The main criticism of the supposed carbon neutrality of bioenergy is that burning biomass releases CO2 immediately, while reabsorption through reforestation can take decades, creating a time lag (Zanchi et al., 2012). Moreover, the origin of the fuel should be considered since the expansion of energy crops can lead to land-use changes that cause deforestation and release additional carbon sequestered in vegetation or soil. Similarly, biomass transport and processing often rely on fossil fuels, increasing the overall carbon footprint. These are some of the reasons some stakeholders and experts question whether bioenergy is inherently emissions-neutral (Booth, 2018). These doubts fuel a negative image for certain groups, while other population segments have little information or interest, reinforcing the wide dispersion in their estimated WTP, and overall lower values than other renewables.

Finally, the distribution of respondents' estimated WTP for geothermal energy is close to zero, perhaps due to an overall lack of familiarity with the technology. For instance, in a DCE about public preferences for RES in Jakarta, Siyaranamual and Yusuf (2024) find that respondents were less familiar with geothermal than with hydropower, solar PV, or wind, and estimated the highest WTP among renewables for solar PV.

The 2023 NECP estimates that over 2024–2030, more than 81.8 billion euros will be needed to finance the transformation of the power plant layout, mainly due to the planned increase in solar PV capacity (MASE, 2024, Table 99). This amount is significantly above the aggregate consumer surplus of Italian households we estimated. This comparison should be interpreted as contrasting elicited household-side welfare gains with the scale of the planned investment effort, rather than as a full social cost–benefit assessment of the NECP.

To assess the extent to which this welfare comparison may depend on sample composition, we conducted a sensitivity analysis using alternative post-estimation weighting adjustments based separately on the national marginal distributions of region, age, and gender. The resulting aggregate consumer-surplus estimates and confidence intervals are remarkably similar across all weighting schemes. Interpreting these values on a bi-monthly household basis and using approximately 26 million households in Italy, the implied aggregate annual WTP remains in a narrow range, between €5.97 and €6.23 billion. This indicates that our main welfare conclusion is robust to these alternative marginal reweighting exercises: even after aligning the sample with key population margins, the aggregate welfare implied by households' preferences remains well below the investment levels envisaged in the NECP.

Even if funding for implementing the NECP comes from other sources, such as the EU budget or private entities, the relationship between the scale of the investment effort and the household-side welfare gains remains policy-relevant. In this context, extending the investment period could bring annual costs and annualized household welfare gains closer to balance by smoothing the same cumulative capital expenditures over a longer horizon and thereby reducing the annual financing requirement. This suggests that while preferences indicate strong support for the transition toward renewables, the pace implied by the 2030 targets may generate short-run costs that exceed the benefits perceived by households. Consequently, our modeling framework can be used to estimate the welfare impacts of more gradual installation pathways that may better align with public WTP.

The policy relevance of this study also extends beyond the aggregate WTP estimate. For example, understanding the heterogeneity of the population's preferences and the factors that influence these differences can help in anticipating which policies will be socially acceptable based on the characteristics of the residents and in designing more targeted policy acceptance campaigns depending on the preference class targeted by the policymaker. The latent classes are policy-relevant and easy to interpret because they largely differ in their primary decision driver (cost, reliability, or technology composition), so they directly indicate which NECP levers are most likely to generate support or resistance across population segments. In our class-allocation results

(Table 4), class membership varies systematically with age (including a nonlinear effect) and gender, and it is also related to not reporting household income. Other socio-demographic variables considered (e.g., education, number of children, region, and reported income) did not yield statistically significant coefficients in the class-allocation equations and were therefore not retained in the final specification.

These findings should be interpreted within the scope of a portfolio-level DCE: we value changes in national technology shares, reliability, and cost, but do not model location-specific (NIMBY) factors such as proximity or landscape impacts. Moreover, although we collected attitudinal and ANA measures, we do not incorporate them into the LCM due to a potential endogeneity problem (Alcorta and Mariel, 2025).

Given that energy and climate policies have time horizons of several years or even decades, and public preferences are unstable and evolve, we believe that studies such as this should be conducted more regularly in each country so that regulators have the most up-to-date information possible. Since the energy transition is a global enterprise, more studies in this line would allow researchers and regulators to analyze the heterogeneity of preferences regarding electricity sources across countries and times and study the factors influencing these differences.

CRediT authorship contribution statement

Peio Alcorta: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Data curation, Conceptualization. **Petr Mariel:** Writing – review & editing, Visualization, Validation, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Jürgen Meyerhoff:** Writing – review & editing, Validation, Supervision, Methodology, Investigation, Conceptualization. **Giovanni Signorello:** Writing – review & editing, Validation, Supervision, Methodology, Investigation, Funding acquisition, Conceptualization. **Maria De Salvo:** Writing – review & editing, Validation, Supervision, Methodology, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

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

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Appendix A. Recent RES policy initiatives affecting Italy

Below, we summarize the most relevant energy policy initiatives, both at the national and international levels, regarding the deployment of RES in Italy in the last decade. Note that the listed policies are packages of measures that typically affect many sectors. We focus only on the renewable energy targets.

- **2015:** The Paris Agreement is a global treaty negotiated by 196 parties at the 2015 United Nations Climate Change Conference to combat climate change. Its main objective is to limit global warming to well below 2°C, preferably 1.5°C, above pre-industrial levels. Through their Nationally Determined Contributions (NDCs), members of the European Union have pledged to reduce greenhouse gas emissions to achieve this goal (UNFCCC, 2015).
- **2017:** The Italian National Energy Strategy (NES) set objectives to reduce final energy consumption by 10 million tonnes of oil equivalent (Mtoe) by 2030, achieve a 28% share of renewables in total energy consumption and a 55% share in electricity consumption by 2030, strengthen the security of the supply, and phase out the use of coal in electricity generation by 2025 (MATTM, 2017).
- **2019:** Italy’s 2019 National Energy and Climate Plan (NECP 2019) is a comprehensive strategy outlining national objectives and measures for energy efficiency, deployment of renewable energy sources, and reductions of greenhouse gas emissions, in line with the European Union’s 2030 climate and energy objectives. It sets the target of generating 30% of final energy consumption from RES by 2030 (MIMIT, 2019).
- **2020:** The European Green Deal (EGD) outlines policies to decarbonize the economy by achieving net zero greenhouse gas emissions by 2050, with a 55% reduction by 2030 compared to 1990 levels, by improving energy efficiency and increasing the use of renewable energy sources. The Commission has set the objective that one-third of the €1.8 trillion investment from the NextGenerationEU and the EU’s seven-year budget be used to finance the Green Deal. As of 2024, this target has been exceeded, reaching 42% (European Commission, 2024).
- **2021:** “Fit for 55” contains a set of measures to enable the EU to meet its 55% emissions reduction target by 2030. The European Council agreed to set a binding EU-level target of 42.5% of energy from RES in the overall energy mix by 2030 (Council of the European Union, 2022).
- **2022:** REPowerEU is an EU initiative to protect consumers and businesses from energy shortages caused by the war in Ukraine. It aims to increase energy security and efficiency by diversifying energy supplies and producing clean energy. A key proposal of the plan is to increase the EU’s 2030 target for penetration of renewable energy from the previous target of 40% to a new target of 45%. As part of this plan, the EU Solar Energy Strategy aimed to deploy more than 320 GW of new solar photovoltaic (PV) power by 2025, doubling the installed capacity at that time, and almost 600 GW by 2030, displacing the consumption of 9 billion cubic meters (bcm) of natural gas annually by 2027 (European Commission, 2022).
- **2023:** Italy’s 2023 National Energy and Climate Plan (NECP 2023) updates the targets from 2019 and sets new, more realistic targets to meet the EU’s climate change ambitions: Renewables should reach 40.5% of Italy’s national final energy consumption and 65% of electricity consumption in 2030, with solar PV becoming the biggest source for renewable electricity with 79 GW of installed capacity, almost quadrupling its capacity from 2021. The final version of this update was completed in 2024 (MASE, 2024).

Appendix B. Sample composition and weighting factors

This appendix reports the population and sample shares used to construct the regional post-stratification weights employed in the main estimations, as well as the marginal weighting factors for age and gender used in the sensitivity analysis (see Tables B.2 and B.3).

Appendix C. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.eneco.2026.109484.

Table B.1
Region-specific post-stratification weights.

Region	Population share (%)	Sample share (%)	Weight
Abruzzo	2.17	2.59	0.84
Basilicata	0.92	1.35	0.68
Calabria	3.10	3.45	0.90
Campania	9.29	8.25	1.13
Emilia Romagna	7.57	9.48	0.80
Friuli Venezia Giulia	2.06	3.33	0.62
Lazio	9.69	8.50	1.14
Liguria	2.62	4.68	0.56
Lombardia	16.90	9.11	1.86
Marche	2.54	2.34	1.08
Molise	0.50	1.11	0.45
Piemonte	7.28	9.61	0.76
Puglia	6.60	6.65	0.99
Sardegna	2.74	4.80	0.57
Sicilia	8.03	9.24	0.87
Toscana	6.29	5.79	1.09
Trentino Alto Adige	1.79	1.11	1.61
Umbria	1.46	2.96	0.50
Valle d'Aosta	0.21	0.12	1.70
Veneto	8.24	5.54	1.49

Note: Weights are defined as the ratio between population and sample shares.

Table B.2
Age-specific marginal weighting factors.

Age group	Population share (%)	Sample share (%)	Weight
18–24	8.26	6.65	1.24
25–34	12.50	18.23	0.69
35–44	14.06	22.91	0.61
45–54	18.26	23.28	0.78
55–64	18.24	17.73	1.03
65–74	13.82	9.73	1.42
75–84	10.20	1.11	9.20
≥85	4.66	0.37	12.60

Note: Weights are defined as the ratio between population and sample shares.

Table B.3
Gender-specific marginal weighting factors.

Gender	Population share (%)	Sample share (%)	Weight
Male	48.44	60.34	0.80
Female	51.56	39.66	1.30

Note: Weights are defined as the ratio between population and sample shares.

References

Abrate, G., Bruno, C., Erbetta, F., Fraquelli, G., Lorite-Espejo, A., 2016. A choice experiment on the willingness of households to accept power outages. Util. Policy 43, 151–164.

Alberini, A., Bigano, A., Ščasnỳ, M., Zvěřinová, I., 2018a. Preferences for energy efficiency vs. renewables: what is the willingness to pay to reduce CO2 emissions? Ecol. Econom. 144, 171–185.

Alberini, A., Š˘ casnỳ, M., Bigano, A., 2018b. Policy-v. individual heterogeneity in the benefits of climate change mitigation: Evidence from a stated-preference survey. Energy Policy 121, 565–575.

Alcorta, P., Mariel, P., 2025. Beyond biases: Exploring endogeneity in the allocation function of latent class models for environmental valuation. Resour. Energy Econ. 83, 101498.

Alcorta, P., Mariel, P., 2026. On the asymptotic variance of latent class logit models for discrete choice applications. J. Choice Model. 58, 100586.

ARERA, 2023. Relazione annuale sullo stato dei servizi e sull'attività svolta (volume 1). (Accessed 29 October 2024) https://www.arera.it/fileadmin/allegati/relaz_ann/23/RA23_volume_1.pdf.

ARERA, 2024. Relazione annuale sullo stato dei servizi e sull'attività svolta (volume 1). (Accessed 29 October 2024) https://www.arera.it/fileadmin/allegati/relaz_ann/24/RA24_vol1.pdf.

Bartczak, A., Budziński, W., Gołębiowska, B., 2021. Impact of beliefs about negative effects of wind turbines on preference heterogeneity regarding renewable energy development in Poland. Resour. Conserv. Recycl. 169, 105530.

Bersano, A., Segantin, S., Falcone, N., Panella, B., Testoni, R., 2020. Evaluation of a potential reintroduction of nuclear energy in Italy to accelerate the energy transition. Electr. J. 33 (7), 106813.

Bigerna, S., Polinori, P., 2014. Italian households' willingness to pay for green electricity. Renew. Sustain. Energy Rev. 34, 110–121.

Bollino, C.A., 2009. The willingness to pay for renewable energy sources: the case of Italy with socio-demographic determinants. Energy J. 30 (2), 81–96.

Booth, M.S., 2018. Not carbon neutral: Assessing the net emissions impact of residues burned for bioenergy. Environ. Res. Lett. 13 (3), 035001.

Borriello, A., Burke, P.F., Rose, J.M., 2021. If one goes up, another must come down: A latent class hybrid choice modelling approach for understanding electricity mix preferences among renewables and non-renewables. Energy Policy 159, 112611.

Bunch, D.S., Gay, D.M., Welsch, R.E., 1993. Algorithm 717: Subroutines for maximum likelihood and quasi-likelihood estimation of parameters in nonlinear regression models. ACM Trans. Math. Softw. (TOMS) 19 (1), 109–130.

Cerdá, E., López-Otero, X., Quiroga, S., Soliño, M., 2024. Willingness to pay for renewables: Insights from a meta-analysis of choice experiments. Energy Econ. 130, 107301.

Chaikumbung, M., 2021. Institutions and consumer preferences for renewable energy: A meta-regression analysis. Renew. Sustain. Energy Rev. 146, 111143.

Cicia, G., Cembalo, L., Del Giudice, T., Palladino, A., 2012. Fossil energy versus nuclear, wind, solar and agricultural biomass: Insights from an Italian national survey. Energy Policy 42, 59–66.

Compagnucci, L., Spigarelli, F., 2023. Alcune riflessioni sulle politiche industriali per la transizione energetica: il ruolo del piano nazionale integrato per l'energia e il clima. "L'Industria, Riv. di Econ. E Politica Industriale" (3/2023), 495–522. http://dx.doi.org/10.1430/112688.

Contu, D., Strazzera, E., 2022. Testing for saliency-led choice behavior in discrete choice modeling: An application in the context of preferences towards nuclear energy in Italy. J. Choice Model. 44, 100370.

Council of the European Union, 2022. "Fit for 55": Council agrees on higher targets for renewables and energy efficiency. (Accessed 29 October 2024) Press Release, 618/22, 27/06/2022, https://www.consilium.europa.eu/en/press/press-releases/2022/06/27/fit-for-55-council-agrees-on-higher-targets-for-renewables-and-energy-efficiency/pdf/.

Cousse, J., 2021. Still in love with solar energy? Installation size, affect, and the social acceptance of renewable energy technologies. Renew. Sustain. Energy Rev. 145, 111107.

Crippa, M., Guizzardi, D., Pagani, F., Banja, M., Muntean, M., Schaaf, E., Monforti-Ferrario, F., Becker, W.E., Quadrelli, R., Risquez Martin, A., Taghavi-Moharamli, P., Köykkä, J., Grassi, G., Rossi, S., Melo, J., Oom, D., Branco, A., San-Miguel, J., Manca, G., Pisoni, E., Vignati, E., Pekar, F., 2024. GHG emissions of all world countries. http://dx.doi.org/10.2760/4002897.

Esposito, L., Romagnoli, G., 2023. Overview of policy and market dynamics for the deployment of renewable energy sources in Italy: Current status and future prospects. Heliyon 9 (7).

European Commission, 2022. REPowerEU with clean energy. (Accessed 29 October 2024) https://ec.europa.eu/commission/presscorner/api/files/attachment/872548/FS_CleanEnergy.pdf.

European Commission, 2024. Achievements of the von der leyen commission: The European green deal. (Accessed 29 October 2024) https://ec.europa.eu/commission/presscorner/api/files/attachment/879667/3%20European%20Green%20Deal.pdf.

Greene, W.H., Hensher, D.A., 2003. A latent class model for discrete choice analysis: contrasts with mixed logit. Transp. Res. Part B: Methodol. 37 (8), 681–698.

Hanemann, W.M., 1984. Welfare evaluations in contingent valuation experiments with discrete responses. Am. J. Agric. Econ. 66 (3), 332–341.

Hayashi, F., 2000. Econometrics. Princeton University Press.

Hess, S., Palma, D., 2019. Apollo: A flexible, powerful and customisable freeware package for choice model estimation and application. J. Choice Model. 32, 100170.

Huh, S.-Y., Woo, J., Lim, S., Lee, Y.-G., Kim, C.S., 2015. What do customers want from improved residential electricity services? evidence from a choice experiment. Energy Policy 85, 410–420.

Hwang, K.-W., Ahn, J., Lee, C.-Y., 2024. Analysis of consumer preferences for community solar programs using choice experiment. Energy Strat. Rev. 54, 101464.

Hynes, S., Hanley, N., Scarpa, R., 2008. Effects on welfare measures of alternative means of accounting for preference heterogeneity in recreational demand models. Am. J. Agric. Econ. 90 (4), 1011–1027.

ISPRA, 2024. Le emissioni di gas serra in italia. Obiettivi di riduzione al 2030. (Accessed 31 October 2024)https://www.isprambiente.gov.it/files2024/pubblicazioni/rapporti/rapporto-399-24-le-emissioni-di-gas-serra-in-italia.pdf.

ISTAT, 2024a. Population and household projections – base 1/1/2023. (Accessed 21 January 2025) https://www.istat.it/wp-content/uploads/2024/07/Population-and-household-projections_Base-I_2023-1.pdf.

ISTAT, 2024b. Resident population by age, sex and marital status on january 1st 2024. (Accessed 14 June 2024) https://demo.istat.it/app/?i=POS&l=en.

Kim, J., Park, S.Y., Lee, J., 2018. Do people really want renewable energy? Who wants renewable energy?: Discrete choice model of reference-dependent preference in South Korea. Energy Policy 120, 761–770.

Klinglmair, A., Bliem, M.G., Brouwer, R., 2015. Exploring the public value of increased hydropower use: a choice experiment study for Austria. J. Environ. Econ. Policy 4 (3), 315–336.

Mariel, P., Campbell, D., Sandorf, E.D., Meyerhoff, J., Vega-Bayo, A., Blevins, R., 2025. Environmental Valuation with Discrete Choice Experiments in R: Guidance on Design, Implementation, and Data Analysis. Springer.

Mas-Colell, A., Whinston, M.D., Green, J.R., et al., 1995. Microeconomic Theory. vol. 1, Oxford university press New York.
MASE, 2024. Piano nazionale integrato per l'energia e il clima. (Accessed 29 October 2024) https://www.mase.gov.it/sites/default/files/PNIEC_2024_revfin_01072024%20errata%20corrige%20pulito.pdf.
MATTM, 2017. Italy's national energy strategy 2017. (Accessed 29 October 2024) https://www.mimit.gov.it/images/stories/documenti/BROCHURE_ENG_SEN.PDF.
Mattmann, M., Logar, I., Brouwer, R., 2016. Hydropower externalities: A meta-analysis. Energy Econ. 57, 66–77.
McConnell, K.E., 1995. Consumer surplus from discrete choice models. J. Environ. Econ. Manag. 29 (3), 263–270.
McFadden, D., 1974. Conditional logit analysis of qualitative choice behavior. Front. Econ. 105–142.
MIMIT, 2019. Piano nazionale integrato per l'energia e il clima. (Accessed 29 October 2024) https://www.mimit.gov.it/images/stories/documenti/PNIEC_finale_17012020.pdf.
Murakami, K., Ida, T., Tanaka, M., Friedman, L., 2015. Consumers' willingness to pay for renewable and nuclear energy: A comparative analysis between the US and Japan. Energy Econ. 50, 178–189.
Oehlmann, M., Meyerhoff, J., 2017. Stated preferences towards renewable energy alternatives in Germany–do the consequentiality of the survey and trust in institutions matter? J. Environ. Econ. Policy 6 (1), 1–16.
Olsen, B.E., 2010. Wind energy and local acceptance: How to get beyond the nimby effect. Eur. Energy Environ. Law Rev. 19 (5).
Ozbafli, A., Jenkins, G.P., 2015. The willingness to pay by households for improved reliability of electricity service in north cyprus. Energy Policy 87, 359–369.
Reichl, J., Schmidthaler, M., Schneider, F., 2013. The value of supply security: The costs of power outages to Austrian households, firms and the public sector. Energy Econ. 36, 256–261.
Sandorf, E.D., Campbell, D., 2023. Spdesign: Designing stated preference experiments. URL: https://CRAN.R-project.org/package=spdesign R package version 0.0.3.
Scarpa, R., Thiene, M., 2005. Destination choice models for rock climbing in the northeastern alps: a latent-class approach based on intensity of preferences. Land Econ. 81 (3), 426–444.
Siyaranamual, M.D., Yusuf, A.A., 2024. Public preferences for renewable energy sources in Indonesia. Sustain. Sci. 1–12.
Terna, 2023. Dati statistici sull'energia elettrica in Italia 2022. (Accessed: 31 October 2024) https://download.terna.it/terna/ANNUARIO%20STATISTICO%202022_8dbd4774c25facd.pdf.
Terna, 2024. Terna dati, statistical data of energy generation, capacity, renewable sources (web portal). (Accessed: 18 December 2024) https://dati.terna.it/en/generation/statistical-data#capacity/renewable-sources.
Tocock, M., Tinch, D., Hatton MacDonald, D., Rose, J.M., 2023. Managing the energy trilemma of reliability, affordability and renewables: Assessing consumer demands with discrete choice experiments. Aust. J. Agric. Resour. Econ. 67 (2), 155–175.
UNFCCC, 2015. Paris agreement. (Accessed: 31 October 2024) https://unfccc.int/sites/default/files/english_paris_agreement.pdf.
Upham, P., Shackley, S., 2007. Local public opinion of a proposed 21.5 MW (e) biomass gasifier in devon: Questionnaire survey results. Biomass Bioenergy 31 (6), 433–441.
van der Horst, D., 2007. NIMBY or not? Exploring the relevance of location and the politics of voiced opinions in renewable energy siting controversies. Energy Policy 35 (5), 2705–2714.
Varian, H.R., 1992. Microeconomic Analysis, 3rd ed. WW Norton & Company.
Vecchiato, D., 2014. How do you like wind farms? Understanding people's preferences about new energy landscapes with choice experiments. Aestimum 64, 15–37.
Vecchiato, D., Tempesta, T., 2015. Public preferences for electricity contracts including renewable energy: A marketing analysis with choice experiments. Energy 88, 168–179.
Vergine, S., del Pino Ramos-Sosa, M., Attanasi, G., D'Amico, G., Llerena, P., 2024. Willingness to accept a wind power plant: A survey study in the south of Italy. Energy Policy 192, 114201.
Wang, Y., Wu, L., Zhou, Y., 2024. Household's willingness to pay for renewable electricity: A meta-analysis. Energy Econ. 131, 107390.
White, H., 1982. Maximum likelihood estimation of misspecified models. Econometrica 50 (1), 1–25. http://dx.doi.org/10.2307/1912526.
Zanchi, G., Pena, N., Bird, N., 2012. Is woody bioenergy carbon neutral? A comparative assessment of emissions from consumption of woody bioenergy and fossil fuel. Gcb Bioenergy 4 (6), 761–772.
Zeng, J., Bao, R., McFarland, M., 2022. Clean energy substitution: The effect of transitioning from coal to gas on air pollution. Energy Econ. 107, 105816.