IRENE Working Paper 20-11

UNIVERSITÉ DE NEUCHÂTEL
Institut de recherches économiques

Beyond political divides: Analyzing public opinion on carbon taxation in Switzerland

Laurent Ott, Mehdi Farsi, and Sylvain Weber

Beyond political divides: analyzing public opinion on carbon taxation in Switzerland*

Laurent Ott† Mehdi Farsi‡ Sylvain Weber§

November 16, 2020

Abstract

This paper investigates public opinion on the Swiss CO_2 levy and its 2020 revision by using a discrete choice experiment answered by a sample of 586 respondents living in Switzerland. The experiment is designed to elicit citizen preferences among various taxation attributes and is followed by a referendum voting experiment on various CO_2 levy proposals. Based on latent class modeling approaches, we find that the population is composed by two distinct but relatively preference profiles: *Environmentalists* and *Neutrals*. Respondents belonging to the first group tend to favor higher carbon tax rates and a redistribution of proceeds benefiting low-income individuals, whereas those in the second group prefer lower rates and a uniform redistribution of proceeds across all taxpayers. Findings from the voting experiment point to a general support among the *Environmentalists*, but an uncertain approval from the *Neutral* group.

Keywords: Carbon tax, preference heterogeneity, public opinion, latent class, discrete choice experiment

JEL classification: C25, D72, D78, H23, Q48, Q54

*This research is part of the activities of SCCER CREST (Swiss Competence Center for Energy Research), which is financially supported by Innosuisse under Grant No. KTI. 1155000154.

†University of Neuchâtel, Institute of economic research, Abram-Louis Breguet 2, 2000 Neuchâtel, Switzerland. laurent.ott@unine.ch

‡University of Neuchâtel, Institute of economic research. mehdi.farsi@unine.ch

§University of Neuchâtel, Institute of economic research. sylvain.weber@unine.ch.

Abbreviation list:

AIC	Akaike information criterion
BIC	Bayesian information criterion
CAIC	consistent AIC
CL	conditional logit
DCE	discrete choice experiment
E-M	expectation-maximization
GHG	greenhouse gas
IIA	independence of irrelevant alternatives
LC	latent class
LCA	latent class analysis
ML	maximum likelihood
MNL	multinomial logit
PCP	posterior class probability
SimLC	simultaneous latent class model
SQ	*status quo*
SHEDS	Swiss Household Energy Demand Survey
tCO_2	ton of CO_2
2SLC	two-step latent class model

1 Introduction

Taxing greenhouse gas (GHG) emissions is a solution favored by many economists for tackling anthropogenic climate change. Such policies nevertheless do not benefit from general public support, as observed for instance in the recent "yellow vests" protests in France[1]. Given that the acceptance of a policy is crucial to its effective long-term implementation (see Dunlap, 1989), the design of environmental policies based on taxation needs to be adapted to public preferences. Securing public support requires understanding of the diversity of the population and the reasons for public resistance among various clusters of society. This is especially valid for environmental taxes, which aim to correct negative externalities. In fact, the proceeds of such taxes are generally earmarked for a specific purpose, as opposed to contributing to general government revenues (see World Bank, 2019). Moreover, these taxes can be used to cut other distortionary taxes, giving rise to a so-called double dividend (Goulder, 1995). Public opinion on carbon taxation is therefore more complex than the usual aversion to taxes, and standard tools like the traditional left versus right political prism alone might not be sufficient to explain it.

Public opinion toward environmental policies has received a lot of attention from scholars (e.g. Dunlap, 1989; Aklin et al., 2013; Valeri et al., 2016; Bakaki and Bernauer, 2018), and much work on this topic underlines the importance of accounting for preference heterogeneity. On the specific case of carbon taxes, although plenty of research has already been carried out (e.g. Kallbekken and Sælen, 2011; Thalmann, 2004; Amdur et al., 2014; Baranzini and Carattini, 2017), little is known about the link between preferences for policy attributes and individual characteristics. A deeper investigation of such links would help policy-makers design optimal taxation schemes and target promotion campaigns to specific population groups. Considering the general public as a monolithic mass instead of a plurality of preferences can indeed induce a loss of useful information on the perception of various aspects of carbon taxes. Studies point to highly probable correlation between environmental preferences and self-reported placement on the conventional left-right political scale (see e.g. Cruz, 2017; Kallbekken and Sælen, 2011; Harring and Jagers, 2013). However, other factors such as environmental attitudes can play an equally important role but have received less attention.

This paper opens with a brief survey of empirical literature on the elicitation of preferences regarding environmental taxation. It also provides a quantitative analysis of individuals' valuation of (or aversion to) various attributes of a carbon taxation scheme using the case of Switzerland's CO_2 levy, a carbon tax applied on non-motor fossil fuels[2]. A main focus is on unraveling systematic relationships between these preferences and a selection of explanatory variables including sociodemographic factors. The possible contrast between conventional political tendencies and environmental preferences is studied via a selection of self-reported measures of attitudes and perceptions.

[1]The "yellow vests movement" (*Mouvement des gilets jaunes*) started in opposition to an intended increase in fuel tax rate. See for instance The Economist (27.11.2018): "What, and who, are France's 'gilets jaunes'?"

[2]In Switzerland, fossil motor fuels are primarily taxed through a petroleum tax independently of their CO_2 content. This might change with the implementation of the new CO_2 law adopted by the parliament in September 2020, depending on whether it is subject to a popular referendum and supported by a majority of voters—which is unknown by the time of writing.

In order to identify how a carbon tax should be designed to receive the maximum public support, we use a discrete choice experiment (DCE). DCEs allow to reveal and compare preferences for different policy attributes. With relatively distinct features in international comparison (World Bank, 2019), the Swiss case lends itself to a realistic DCE. First, the tax rate has gradually increased since its introduction in 2008, from CHF 12 to CHF 96 per ton of CO_2 (tCO_2) and it could legally be raised to a maximum of CHF 120. Moreover, as of 2020, the Swiss CO_2 levy is under revision by the parliament, with a proposed increase in its maximum potential rate from CHF 120 to CHF 210 per tCO_2. Second, the proceeds are redistributed in the form of building retrofit subsidies through the government's *Building Program* (one third) and lump-sum payoffs to individuals and firms (two thirds)[3]. It is fair to consider that the public has experience with the existing system and could realistically evaluate a departure thereof. Third, the CO_2 levy has a positive net financial impact for certain individuals, depending on their consumption of non-motor fossil fuels—i.e. mainly heating oil and natural gas[4]. This feature provides a context with more or less clear potential "winners" and "losers" among households.

Data from the DCE are analyzed with latent class (LC) models. The results reveal two classes that correspond to distinct *citizen profiles*, which we dub as *Environmentalists* and *Neutrals* on the basis of their response patterns and self-reported perceptions and attitudes. Results also highlight the contrasting differences between the two groups. In particular, if members of the first group show a preference for *higher* tax rates and a redistribution of proceeds benefiting low-income households, the other group favors lower tax rates and uniform transfers. Whether a revision of the CO_2 levy would be accepted in a referendum is however uncertain: if the first class is likely to accept it, the second one does not display any particular support.

The adopted approach goes one step beyond the existing literature (e.g. Sælen and Kallbekken, 2011; Carattini et al., 2017), as it explicitly accounts for the origin of preference heterogeneity in the model. The results demonstrate the benefits of choice experiments, particularly in the segmentation of the population in groups with different preferences, and further research should thus acknowledge the probable presence of clustered heterogeneity in the population.

The remainder of this paper is structured as follows. Section 2 reviews the relevant literature. Section 3 presents the experiment and the dataset. Section 4 explains our modeling approach. Section 5 presents the results. Finally, Section 6 discusses policy implications and concludes.

[3]The total amount redistributed to individuals (firms) comes from the tax proceeds collected from individuals (firms). Each Swiss resident receives a uniform lump sum under the form of a rebate on their health insurance bills, whereas each company gets an amount proportional to its total payroll.

[4]According to the latest data available from the Federal Statistical Office's *Buildings and Dwellings statistics*, about 60% of the residential buildings used heating oil (39.4%) or natural gas (20.7%) for heating in 2017. Similar figures were obtained in the *Swiss Household Energy Demand Survey* (see Burger et al., 2018). Therefore, a substantial share of about 40% of the Swiss households use non-fossil fuels for heating, and these are among the net beneficiaries (along with possibly some of the small consumers) from the CO_2 levy.

2 Public opinion on environmental policy

2.1 Conceptual framework

The literature on public opinion toward policies uses varying expressions to qualify its object of study. Even though some authors use them interchangeably, we adhere to the definitions proposed by Dreyer and Walker (2013), who distinguish between three concepts: acceptability, acceptance, and support. Acceptability and acceptance represent passive behaviors without commitment such as a stated willingness-to-accept for a policy measure or willingness-to-pay for a mitigation project, whereas support is an active stance in terms of intent or action, like revealed financial contribution, participation in social movements or voting in favor of a specific policy.

Dreyer and Walker (2013) propose a further distinction between acceptability and acceptance, applying the former to policies *prior* to their implementation, while considering the latter for *already implemented* policies. In the case of incremental changes to existing policies, the timing distinction between acceptability and acceptance could seem irrelevant, as the two become interlinked. The likely presence of a *status-quo* bias (see Fernandez and Rodrik, 1991; Samuelson and Zeckhauser, 1988) and a temporal effect of experiencing a policy on its acceptance also makes this distinction useless in many circumstances where policies change progressively. Therefore, in this paper we distinguish between acceptance and support, while leaving out the distinction between acceptability and acceptance, the former being less useful in the context we consider—i.e. the reform of an already implemented carbon tax.

Another useful distinction needs to be made between public acceptance and social acceptance. Whereas the former refers to the “aggregated degree of acceptance by individual citizens” (Wolsink, 2018, p.288), the latter is a multidimensional and dynamic construct encompassing different aspects of acceptance. When considering the acceptance of renewable energy innovations, Wüstenhagen et al. (2007) distinguish between three dimensions: socio-political acceptance (by key stakeholders, the general public and decision-makers), community acceptance (by local stakeholders, residents and authorities) and market acceptance (by consumers, producers and investors). Wolsink (2010) argues that this conceptual framework can also be applied to other types of policies such as climate change adaptation strategies. Carbon taxation can, to some extent, fit into this framework, especially regarding the socio-political and market dimensions; community acceptance is less relevant because such environmental policies usually have no specific local impacts, unlike the construction of a wind farm, for instance. Social acceptance is thus more complex than public acceptance, which is only one of its multiple aspects. In our study, given that our primary interest is to investigate preferences of Swiss residents, we only consider *public* acceptance (and support) of carbon taxes, not its *social* acceptance.

2.2 The role of individual characteristics

Empirical studies generally consider public opinion regarding environmental policy in one of two ways: they either focus on individual characteristics and preferences to explain environmental concern[5], or look at policy design elements and their effects on public opinion[6]. The relatively limited coverage of environmental policies does not provide sufficient variations to allow for the identification of the effect of policy attributes on support and acceptance using real-world data. In fact, most studies addressing the effect of policy attributes rely on stated preferences data collected through hypothetical experiments. Such experimental data moreover provide insights about the interactions between individual characteristics and policy attributes, which is not addressed in many studies. Experimental studies are discussed in more details in the next section dealing with carbon taxation; here, we focus on the effects of individual characteristics.

The importance of individual characteristics in explaining preferences about environmental policies is well documented. In particular, political orientation and partisanship seem to play a central role. Studying a body of US college students, Dunlap (1975) is among the first to report a clear association between political orientation and environmental concern, suggesting a positive (negative) association of environmentalist preferences with political inclination to the left (right). This finding is confirmed by numerous further studies (Cruz, 2017). Trust in politics and authorities is also positively linked to support of environmental policies such as higher carbon tax rates (Hammar and Jagers, 2006; Harring and Jagers, 2013; Wan et al., 2017).

Socioeconomic factors such as gender, age, income, education, and residential environment are among the most frequently included covariates. Table 1 summarizes the patterns of associations with environmental concern found in a selection of studies. In general, the positive association with education, living in a densely populated area seems to be conclusive. On the other hand, possible associations with gender, age, and income remain ambiguous.

Econometric models can be used to characterize environmental preferences in an empirical setting. In particular, stated preference data can be used to identify distinct clusters of individuals with relatively homogeneous preferences, referred to as latent classes (LC). This approach, also known as latent segmentation, is in line with the premise that individuals with similar preferences coordinate their actions in a small number of political parties. The LC approach, though uncommon in carbon taxation studies, has been used extensively in other environmental studies. Two variants can be observed. In the first variant, the LC model is applied to a single DCE outcome to specify a finite mixture model (more on this below). The second variant is the LC application to a selected number

[5]We consider here a measure for the broad public concern for environmental quality, as defined by Dunlap (1975). Referring to this as the "environmental concern", Dunlap's definition encompasses public perception of environmental issues, support for environmental policies, as well as acceptance measures such as willingness to pay for pollution abatement, among others. This concept helps to draw generalities on the whereabouts of its components, among which public opinion on environmental policies.

[6]Drews and van den Bergh (2016) also underline the role played by contextual factors such as weather, social norms, economic conjecture or media coverage and framing of climatic issues, but our data do not allow us to integrate such aspects in our analysis. We therefore do not cover them in the present literature review.

Table 1: Factors influencing environmental concern

Reference	Gender: female	Age	Income	Education	Living in a city	Political orientation (L to R)	Trust in authorities
Aklin et al. (2013)	+	?	∩	+	∼	·	·
Ercolano et al. (2014)	−	∼	∩	+	·	−	+
Harring and Jagers (2013)	·	·	∼	·	+	−	+
Hsu et al. (2008)	+	·	+	+	·	·	·
Kallbekken and Sælen (2011)	−	·	+	·	·	−	+
Leiserowitz (2006)	?	·	·	+	·	−	·
Rotaris and Danielis (2019)	+	−	+	+	+	−	·
Schumacher (2014)	∼	−	·	+	·	·	·
Swenson and Wells (1997)	∼	∼	+	+	+	·	·
Thalmann (2004)	∼	−	?	+	+	−	·
Torgler and García-Valiñas (2007)	+	−	∩	+	+	−	·
Van Liere and Dunlap (1980)	?	−	?	+	+	−	·
Ziegler (2017)	?	?	·	∼	·	−	·

Notes: +/− indicates a positive/negative association; ∩ indicates an inverted U-shape association; ∼ indicates an absence of association; ? indicates an ambiguous association. L/R stands for left/right political orientation.

of individual measures of environmental preferences. The latter can be used independently of DCE outcomes, or in combination with them. We will clarify the distinction in the following section.

The usefulness of the two LC variants is illustrated by the following examples. First, Rhead et al. (2018) use a LC model to create a typology of environmental attitudes in the UK. Their findings suggest that a prior clustering based on response patterns in a questionnaire can significantly increase the prediction power of environment-related behaviors. Second, Blasch and Farsi (2014) show that LC models outperform other models in analyzing results from a DCE for identifying the willingness-to-pay for voluntary carbon offsets in Switzerland. In fact, their results point to a possibility of misleading willingness-to-pay estimates with other models.

2.3 Carbon taxation and stated preferences

Carattini et al. (2018) provide a thorough review of a large number of studies on public attitudes toward carbon taxes. They conclude that higher tax rates generally induce a resistance among the public (see e.g. Thalmann, 2004; Brännlund and Persson, 2012; Carattini et al., 2017). However, they also observe that, in numerous studies, earmarking tax revenues for environmental purposes increases acceptance (e.g. Sælen and Kallbekken, 2011; Gevrek and Uyduranoglu, 2015), as does redistributing them progressively to households (see for instance Gevrek and Uyduranoglu, 2015; Brännlund and Persson, 2012). Cutting other taxes to benefit from a double dividend seems to be a less popular solution, though. These stylized facts provide essential information on the potential features of a desirable carbon tax, which could be used in various survey designs.

There is also suggestive evidence of a gradual increase in acceptance once the taxes enter into force. For instance, Murray and Rivers (2015) find an increase in the acceptance of British Columbia's carbon tax three years after its implementation. Noting that acceptance increase has been observed in other environmental taxation domains such as waste taxes, Carattini et al. (2018) relate such improvements to experience. Thus, in contrast with many predictions, overcoming oppositions to carbon taxation appears possible.

From a methodological perspective, most studies use stated preference methods, which range from self-reported attitudes and preferences in response to direct survey questions (e.g. Harring and Jagers, 2013; Dreyer and Walker, 2013) to experimental methods such as contingent valuations and discrete choice experiments (e.g. Sælen and Kallbekken, 2011; Rotaris and Danielis, 2019). Our focus is on the few studies that used DCEs. These experiments allow a random variation in attributes, thus offering a great potential for the identification of the relative effects of various policy attributes and the investigation of how individual characteristics interact with policy attributes. In particular, we focus on five studies, three of which (Brännlund and Persson, 2012; Carattini et al., 2017; Beiser-McGrath and Bernauer, 2019) focus exclusively in tax attributes while the other two (Sælen and Kallbekken, 2011; Gevrek and Uyduranoglu, 2015) account for interaction effects with individual characteristics.

In their analysis of the Swedish case using mixed logit models, Brännlund and Persson (2012) report a decrease in acceptance when the personal cost of carbon taxation increases, as well as a distaste for a regressive distribution of the costs to society. They also find that citizens generally prefer the abatement of CO_2 emission to be done in the rest of Europe rather than locally in Sweden. Carattini et al. (2017) analyze data from a DCE conducted in Switzerland and find that higher tax rates reduce acceptance, while redistributing proceeds as lump-sum transfers or social cushioning increase it. They however find that environmental earmarking has either no or a negative impact on acceptance, a result that contradicts most previous findings on the issue. Beiser-McGrath and Bernauer (2019) investigate preferences for carbon tax attributes with a DCE carried out in Germany and the United States and contrast the results they obtain in the two countries. They find that revenue recycling increases respondents' willingness-to-pay at levels likely to induce a significant lowering of GHG emissions in both Germany and the USA. They also notice that support is larger in the US than in Germany and relate this result to the lower social cost of carbon in Germany than in the US (see Ricke et al., 2018).

Sælen and Kallbekken (2011) conduct a DCE on hypothetical fuel tax increases in Norway. They incorporate attitudinal variables in their mixed logit model and interact them with dummies indicating the proposed uses of additional revenues (redistribution or environmental earmarking). Their findings suggest that earmarking revenues for environmental purposes increases acceptance from people who expect to benefit from earmarked revenues, as well as from people who do not expect fuel taxation to be effective *per se*. They also find that redistributing revenues increases acceptance, but less strongly than environmental earmarking. In their DCE carried out in Turkey, Gevrek and Uyduranoglu (2015) add interaction terms between education, employment status and environmental awareness and the attribute levels of their carbon tax proposals, and also use as alternative method a LC model to account for the heterogeneity of respondents' profiles. They find that individuals with higher environmental awareness are significantly more likely to choose a proposal with a progressive redistribution of revenues or with revenues earmarked for environmental purposes. Their LC model identifies two classes: the first one consists in individuals who are more likely to be employed, who have a higher level of education and who are more environmentally aware than the second one. The first class shows preference for a progressive redistribution of tax revenues or for earmarking in favor of environmental policies, whereas the second class shows weaker support for those attributes but prefers earmarking revenues for income redistribution. The second class also displays stronger distaste for the costs induced by carbon taxes than the first class. Results from the LC model hence generally corroborate those from the model with interaction terms, but also provide a more subtle understanding of the heterogeneity of preferences for carbon tax attributes.

As shown by this literature overview, the analysis of DCE data can be carried out with a variety of econometric models dubbed as random utility models. Given the strong heterogeneity in individual preferences, many researchers favor models that can account for unobserved heterogeneity by including random parameters (e.g. mixed logit model) or a finite mixture of coefficients (latent class logit model). The latter approach is particularly interesting as it allows correlation between preference heterogeneity and explanatory variables, an advantage over random parameter models which assume heterogeneity to follow a pre-determined continuous distribution across individuals (see Greene and Hensher, 2003). Moreover, the LC models can readily be extended to include additional meaningful covariates providing a more subtle characterization of the public opinion with respect to various individual factors, as in Gevrek and Uyduranoglu (2015). Such extensions are possible in random-coefficient models but require an increasing number of coefficients, which could render the estimations intractable for estimation and interpretation.

In the following sections we present an application to the case of CO_2 taxation in Switzerland. Throughout this application, we provide more details about various methodologies and illustrate their relative merits. Our focus is upon experimental data—more precisely a DCE—and the LC approach, in particular its potential use for characterizing public opinion beyond the usual political left-right scale. With an ongoing debate on possible reforms of an existing taxation scheme and potential future referenda, the context of Switzerland—at the time of writing—lends itself to an analysis of acceptance as well as support via voting behavior.

3 Experiment Design and Data

Our analysis relies on stated preference data from a sample of 586 Swiss respondents. These data are collected through a DCE conducted within the 2019 wave of the *Swiss Household Energy Demand Survey* (SHEDS)[7].

The experiment is structured into two consecutive stages aiming to identify measures of acceptance and support, respectively. In the first stage, a series of six choice tasks is displayed. Each task is composed of three CO_2 levy proposals, among which one corresponds to the *status quo* (SQ), that is, the current CO_2 levy. In each choice task, respondents are asked to select the proposal they prefer.

Each proposal is defined by four attributes capturing the main features of the CO_2 levy:

[7]See Weber et al. (2017) for more details. The SHEDS sample is constructed to be representative of the Swiss population in terms of gender (female or male), age group (18-34, 35-54, 55+), linguistic region (French or German-speaking) and living situation (home-owner or tenant).

1) Maximum tax rate, i.e. the highest potential tax rate that can legally be levied[8].
2) Share of tax proceeds redistributed to individuals as direct transfers, with the remaining share for public subsidies.
3) Redistribution method (only for non-zero distributed share) defining the transfers as uniform lump sums (the current method) or progressive (i.e. inversely proportional to income).
4) Recipient of subsidies (only when subsidy share is non-zero): *Building Program* (current state), foreign aid for the environment, or local community initiatives.

Chosen attribute levels are displayed in Table 2. The maximum tax rate is displayed both in CHF per tCO_2 and in CHF per 100l of heating oil or 100kg of natural gas. An example of a choice task is displayed in Figure 1.

Table 2: Attribute levels

Maximum tax rate	Shares: redist.—sub.	Redistribution method	Recipient of subsidies
⋄ CHF96 (25.45 per 100l)	⋄ 0%—100%	⋄ Uniform lump-sum	⋄ Building Program
⋄ CHF120 (31.80 per 100l)	⋄ 33%—67%	⋄ Inversely proportional to income	⋄ Foreign aid for the environment
⋄ CHF160 (42.40 per 100l)	⋄ 67%—33%		⋄ Local community initiatives
⋄ CHF210 (55.65 per 100l)	⋄ 100%—0%		
⋄ CHF270 (71.55 per 100l)			

Note: Underlined attribute levels indicate the characteristics of the current CO_2 levy (SQ).

Figure 1: Example of choice task

	Proposition 1	**Proposition 2**	**Status quo**
Maximum tax rate	CHF 160 (CHF 42.40 per 100l heating oil/100kg gas)	CHF 270 (CHF 71.55 per 100l heating oil/100kg gas)	CHF 120 (CHF 31.80 per 100l heating oil/100kg gas)
Redistribution: - Share - Method	0% -	33% Inversely proportional to income	67% Lump-sum
Subsidy: - Share - Beneficiary	100% Local community initiatives	67% Foreign aid for the environment	33% Building program

The second stage of the experiment aims to measure the respondent's support in a possible vote, which is a realistic outcome in Switzerland. In this stage, which follows the choice tasks, the respondents are asked to give their vote in a hypothetical referendum. Each respondent is provided with maximum three choice tasks (hereafter referred to as the "vote task"), each representing one tax proposal. The presentation of attributes is identical to that of the choice tasks in the first stage (as in Figure 1). These tax proposals are randomly selected from the tax options that the respondent has selected as preferred alternatives in the first stage's choice tasks. The set of proposals always contains

[8] In Switzerland, the rate of the CO_2 levy increases when CO_2 emission abatement targets are not met at certain dates set in advance. The maximum tax rate is thus the ceiling that legally limits these increases.

the SQ, even for those who never selected it in the first stage of the experiment. For each respondent, the proposals are displayed one by one. In each vote task, respondents can answer either *Yes*, *No* or *Abstain*.

The experiment also includes a preliminary section prior to the choice tasks and a series of follow-up questions. In the preliminary section, the CO_2 levy and the whereabouts of its reform—then under discussion in the parliament—are presented. This section includes tailored information on how carbon taxation specifically impacts the respondents depending on their current heating system. The follow-up questions are designed to assess the respondents' perception of the DCE (e.g. difficulty to respond or attribute non-attendance) and their general opinion on carbon taxation (e.g. the efficiency of taxing GHG emissions to lower them). Overall, attribute non-attendance does not seem to be particularly prevalent, although more than 57% of respondents found it hard to choose the proposals they preferred. We therefore expect the data to adequately capture the preferences of the respondents.

4 Econometric approach

In line with random utility theory (McFadden, 1974b; Manski, 1977), we assume that respondents make their decision on the basis of a stochastic utility function and a separable random term. In other words, each individual i facing alternative j in choice task t maximizes a random utility function of the form $U_{ijt} = V_{ijt} + \varepsilon_{ijt}$, where V_{ijt} is a deterministic component specified by observables and ε_{ijt} is a residual term representing idiosyncratic variations.

The deterministic component V_{ijt} can be written as:

$$V_{ijt} = x'_{ijt}\beta \tag{1}$$

where x_{ijt} is a vector of independent variables and β is a vector of parameters representing the marginal utility of corresponding attributes. In addition to alternative j's attributes for respondent i, x_{ijt} could include interaction terms between attributes and respondent characteristics. In our model, this vector includes a SQ dummy in addition to the attributes presented in Table 2.

We use the conditional logit (CL) model proposed by McFadden (1974b). Another closely related model is the multinomial logit (MNL) model (see McFadden, 1974a) that is readily adapted to labeled options—hence providing alternative-specific marginal utilities for each attribute. However, the distinction between CL and MNL models is more conceptual than technical, because the two models can be nested in a single general framework (see for instance Hoffman and Duncan, 1988).

Let $c_{ijt} = 1$ when individual i selects option j in task t, and 0 otherwise. The probability that alternative j is selected by individual i in choice task t in the CL model is defined as

$$P\left(c_{ijt} = 1\right) = \frac{e^{x'_{ijt}\beta}}{\sum_j e^{x'_{ijt}\beta}} \tag{2}$$

where β is the vector of model parameters to be estimated.

The basic CL model assumes that the utility parameters β are the same for all respondents. This assumption could be restrictive for capturing the strong heterogeneity usually observed in individual preferences. Relaxing this assumption is crucial for identifying the diversity of preferences in our data. Moreover, a corollary of this assumption in a logit model is odds-proportionality, hence the independence of irrelevant alternatives (IIA) restriction. An additional advantage of integrating heterogeneous parameters among respondents is to relax the IIA restriction.

To account for heterogeneity of preferences in the population, we use three different approaches, which are presented in Table 3. The first one relies on a Mixed (or random coefficient) model, in which the coefficients are assumed to follow a continuous distribution (usually normal) across individuals (Hensher and Greene, 2003). Covariates can also be included as interaction terms.

Our second and third approaches are based on the latent class CL model (LC-CL). In this type of models, unobservable clusters denominated as latent classes are identified based on answer patterns to a set of clustering variables. As explained by Greene and Hensher (2003), LC models assume that parameters are discretely distributed across a certain number of classes $s = 1, ..., S$, with no specific distribution assumption on classes. The number of latent classes is decided by fitting models with an increasing number of classes and by comparing them using statistical criteria such as the Akaike or Bayesian information criteria (AIC or BIC, see Tein et al., 2013). Individual LC membership probabilities $\pi_{is} = P(i \in s)$ are usually modeled with a separate MNL model with respondent characteristics z_i as covariates (see Greene and Hensher, 2003).

The LC model contrasts with the Mixed model in that the Mixed model assumes a continuous distribution of utility parameters across individuals with a specific pre-assumed functional form, whereas the LC model posits no distribution assumption. The random distribution of parameters in the Mixed model is also required to be uncorrelated with the actual outcomes. However, there is no restricting condition on the fixed parameters in the LC model. This could be an important advantage for the LC approach, because the heterogeneity of preferences could be correlated with the utility parameters. For instance, respondents who have a lower marginal valuation of taxes could be more likely to opt for the SQ option.

We use two variants of the LC-CL model: the simultaneous LC-CL (SimLC) model and the two-step LC-CL (2SLC) model. In the SimLC model, π_{is} are estimated simultaneously to class-specific preference parameters β_s (see Table 3): stated preference data from the DCE are used as clustering variables. The 2SLC model is an extension of the model proposed by Patunru et al. (2007). LC membership probabilities $\tilde{\pi}_{is}$ are estimated in a first step using attitudinal and perception-related variables regarding the environment and environmental policy as clustering variables instead of stated preferences from the DCE. Then, predicted $\tilde{\pi}_{is}$ are introduced in the likelihood function as exogenous parameters to estimate preference parameters $\tilde{\beta}_s$ in a second step. This procedure has the advantage of being consistent with McFadden's (1986) theoretical framework on decision-making: exogenous factors—such as socioeconomics—shape attitudes and perceptions, which in turn jointly shape choice preferences. In our case, resulting LCs can be understood as modeling the different *citizen profiles* of respondents regarding environmental policy, analogously to Rhead et al. (2018). However, $\tilde{\pi}_{is}$ do not maximize the fit of the choice model, unlike π_{is} in the SimLC model. It should be noted that the

Table 3: Econometric models

Model	Assumptions	Model parameters	Log-likelihood function	Estimation method	Modeling of heterogeneity	References
Conditional logit (CL)	Odds-proportionality	β	$\sum_i \log \left\{ \prod_t \prod_j \left(\frac{e^{x'_{ijt}\beta}}{\sum_j e^{x'_{ijt}\beta}} \right)^{c_{ijt}} \right\}$	ML	No modeling of heterogeneity in parameters	McFadden (1974b)
Mixed logit	Random coefficients, no correlation between random parameters	$\beta_i = \beta + z'_i\gamma + \omega_i$, $\omega_i \sim N(0, \Sigma)$	$\sum_i \log \left\{ \int \left[\prod_t \prod_j \left(\frac{e^{x'_{ijt}\beta_i}}{\sum_j e^{x'_{ijt}\beta_i}} \right)^{c_{ijt}} \right] f\left(\beta_i\right) d\beta_i \right\}$	Simulated ML	Modeling of preference heterogeneity as continuous and random, arbitrary choice of distribution	McFadden and Train (2000); Hensher and Greene (2003)
Simultaneous latent class CL (SimLC)	LC inferred from choice data	$\beta_s,\ \pi_{is} = \frac{e^{z'_i\gamma_s}}{\sum_s e^{z'_i\gamma_s}}$	$\sum_i \log \left\{ \sum_s \pi_{is} \left[\prod_t \prod_j \left(\frac{e^{x'_{ijt}\beta_s}}{\sum_j e^{x'_{ijt}\beta_s}} \right)^{c_{ijt}} \right] \right\}$	E-M and ML	Clustered (discrete) heterogeneity modeled with covariates and consistent with choice data	McCutcheon (1987); Greene and Hensher (2003)
Two-step latent class CL (2SLC)	LC inferred from attitudes and perceptions	$\tilde{\beta}_s,\ \tilde{\pi}_{is} = \frac{e^{z'_i\tilde{\gamma}_s}}{\sum_s e^{z'_i\tilde{\gamma}_s}}$	$\sum_i \log \left\{ \sum_s \tilde{\pi}_{is} \left[\prod_t \prod_j \left(\frac{e^{x'_{ijt}\tilde{\beta}_s}}{\sum_j e^{x'_{ijt}\tilde{\beta}_s}} \right)^{c_{ijt}} \right] \right\}$	E-M and ML	Clustered (discrete) heterogeneity modeled with covariates and independent of choice data	Patunru et al. (2007)

β is a vector of estimated marginal utility parameters; $f(\cdot)$ is the multivariate normal distribution function; z_i is the vector of respondent characteristics; ω_i is a vector of random parameters with Σ as covariance matrix; π_{is} is the probability that individual i belongs to class $s = 1, ..., S$. ML = maximum likelihood; E-M = expectation-maximization algorithm (see Morey et al., 2006).

SimLC models used to analyze data from the choice tasks and the vote tasks are independent, while the same $\tilde{\pi}_{is}$ are used for both types of data in the 2SLC model.

Clustering variables used in the first step of the 2SLC model include some key factors capturing respondents' perceptions and attitudes regarding the environment and environmental policy. A full description is provided in the lower part of Table A1. The first variable is the willingness-to-adopt an environmentally-friendly behavior despite the inconveniences it might cause, while the second is the feeling of being unable to lower one's GHG emissions. These two variables relate to attitudes toward the environment. The third is the trust in information on energy and energy-saving provided by scientists. This variable captures the extent of the confidence (or skepticism) respondents have regarding "official" information. The fourth is the perception that carbon taxes are effective to lower CO_2 emissions from firms and individuals. Respondents are assigned to four groups: those who consider taxing CO_2 emissions is efficient in both cases, those who believe it is only efficient for firms, those who only believe it is efficient for individuals, and those who do not consider this policy as efficient at all. The last variable is whether the respondent supports the *School strike for climate* movement. It is taken as an indicator of the degree of agreement with the position that more ambitious actions to fight anthropogenic climate change need to be taken without further delay.

We integrate further respondent characteristics—covariates z_i—as determinants of the variation of utility parameters in our models. These covariates consist of socioeconomic, geographic and political variables. Our choice of variables is guided by the literature discussed in Section 2. In particular, we use gender and age groups, higher education, residential environment, linguistic region, and political orientation. A full description is provided in the upper part of Table A1. These covariates capture the main personal-level factors that might influence class membership probabilities[9].

We compare results using both the SimLC and the 2SLC approaches to analyze data from our DCE, as they complement each other thanks to the respective strengths and weaknesses presented above. We also contrast these results with those from the CL and the Mixed CL models. This allows to highlight the importance of modeling heterogeneity with observed variables to better understand preferences and their determinants.

[9]Income is not included because numerous respondents (44 out of 586) did not provide this information, causing an important loss of observations. Moreover, if included, its impact on class membership probabilities is not statistically significant. We also tested for the impact of being home-owner and of whether the respondent uses oil or gas for heating, but both variables did not have any impact on results and have thus been dropped.

5 Results

5.1 Descriptive statistics

The first and last columns of Table A2 present descriptive statistics for the sample used in the analysis and for the Swiss population[10]. Males and middle-aged people are slightly overrepresented in our sample in comparison to the Swiss population. It also appears that more educated, rural people, and Swiss nationals are overrepresented in our sample.

5.2 Latent class analysis

Before conducting the regression analysis, the optimal number of (latent) classes needs to be determined for the LC models[11]. Models with the lowest BIC and adjusted BIC (Sclove, 1987) are selected, following Nylund et al.'s (2007) recommendations. Models with two classes generally perform best in terms of these two information criteria (see Table 4) and this solution is therefore chosen. Diagnostics of the LCA for the two-class models are presented in Table 5.

Table 4: LCA: Information criteria

	SimLC (choice)		SimLC (vote)		2SLC	
No. of classes	BIC	Adj. BIC	BIC	Adj. BIC	BIC	Adj. BIC
1	6975.32	6949.90	2278.88	2253.47	6167.78	6132.86
2	6170.19	6109.82	2213.28	2152.92	6017.16	5944.14
3	6241.93	6149.79	2361.62	2269.49	6055.44	5944.33
4	6369.33	6245.41	2425.29	2301.40	6109.56	5960.36

Notes: For the 2SLC model, the information criteria of the first step, i.e. the estimation of $\tilde{\pi}_{is}$, are displayed. Covariates are not included in any model.

Table 5: LCA: Diagnostics

			Avg. PCP		Min. PCP		Max. PCP		Class size	
Model	Entropy	$[\pi_{is} > Q]$	Class A	Class B	Class A	Class B	Class A	Class B	Class A	Class B
SimLC (choice)	0.851	88.23	96.41	95.65	51.06	50.44	100.00	100.00	48.65	51.35
SimLC (vote)	0.763	82.08	96.45	78.93	50.16	50.46	100.00	99.60	77.67	22.33
2SLC	0.674	80.20	91.57	88.75	50.22	50.07	100.00	99.99	53.60	46.40

Notes: All statistics except entropy are expressed in percentages. PCP stands for posterior class probability.

Diagnostics of the LCA conducted for the SimLC model on choice data show that the split between the two classes is clear for this model: the share of respondents Q with a class membership probability π_{is} at least as high as Q is slightly above 88%, which means that more than 88% of respondents belong

[10] Statistics for Switzerland are obtained from databases of the Swiss Federal Office of Statistics, namely the *Population and households statistics* and the *Structural survey*.

[11] LCAs for the two SimlC models have been performed with `R`'s package `apollo` (Hess and Palma, 2019), while the LCA conducted for the first step of the 2SLC model has been carried out with `R`'s package `poLCA` (Linzer and Lewis, 2011). `poLCA` allows for missing values in the clustering variables, so that no observation needs to be dropped from the sample.

to a class with a probability of at least 88%. The average posterior class probabilities (Avg. PCP)[12] for Classes A and B are both about 96%. The relative entropy[13] of the model is also high, at about 0.85. The size of the two classes is also quite even, with an estimated average probability of belonging to Class A of 49% and to Class B of 51%.

The SimLC model on vote data performs less well in that regard, as the split between the two classes appears as less clear-cut. The size of Classes A and B is very unequal, as the former accounts for more than three quarters of the sample. Diagnostics for the 2SLC model are also less good than for the SimLC model on choice data, but the size of the two classes is more balanced than for the SimLC model on vote data. The average PCPs of the 2SLC model also suggests that respondents generally have a high probability of belonging to the class they would modally be assigned to.

Results from the logistic regression of class membership probabilities on covariates are presented in Table 6. LCA in the SimLC model on choice data shows that being aged over 55 and self-identifying as rightist in politics decrease the probability of belonging to Class A. Other covariates have no statistically significant effect. LCA for the SimLC model on vote data shows that having a tertiary level of education increases the probability of belonging to Class A for this model, but only with a weak statistical significance. LCA for the 2SLC model shows that having a tertiary level of education increases the probability of belonging to Class A, while a right-wing political orientation decreases it. Living in a urban area also has a weakly significant positive effect. Coefficients for other variables are not significant in any of the models.

Table 6: LCA: Regression results

	Constant	Female	Age: 18-34	Age: 55+	Tertiary edu.	City	Countryside	Romandie	Political orientation
SimLC: choice	1.28***	0.06	0.29	−0.57***	−0.02	0.25	0.23	0.02	−0.32***
	(0.39)	(0.19)	(0.25)	(0.21)	(0.19)	(0.22)	(0.27)	(0.23)	(0.06)
SimLC: vote	1.17**	−0.13	−0.54	−0.03	0.54*	0.04	−0.51	−0.01	0.03
	(0.52)	(0.26)	(0.38)	(0.30)	(0.28)	(0.32)	(0.35)	(0.30)	(0.08)
2SLC	2.66***	0.45	0.25	−0.36	0.63**	0.60*	0.21	0.34	−0.77***
	(0.57)	(0.28)	(0.35)	(0.30)	(0.27)	(0.31)	(0.37)	(0.31)	(0.10)

Notes: ***p-value < 0.01; **p-value < 0.05; *p-value < 0.1. MNL coefficients for Class A.

To better understand the nature of the classes, it is necessary to look more closely at their characteristics. Central columns of Table A2 display some descriptive statistics on the latent classes and Table 7 presents the distribution of the clustering variables used in the 2SLC model for each class in all three models. As can be seen in Table 7, patterns of answers[14] differ between the SimLC models on choice and vote data for each class, but they are more similar between the SimLC model on choice data and the 2SLC model. Beyond these differences, relative frequencies of answers for the three models show that, in general, Class A is composed of more environmentally-friendly respondents, while Class B seems more neutral in that regard. The two aforementioned citizen profiles thus schematically cor-

[12]The average posterior class probability is, for each class, the average class membership probability of respondents modally assigned to it (Masyn, 2013).

[13]Relative entropy is an index of the model's overall precision in the assignment of respondents to classes: a value of 1 indicates perfect assignment—i.e. all respondents belong to a class with a probability of 1—and a value of 0 means that the model is not better than a random guess (Masyn, 2013; Ramaswamy et al., 1993).

[14]There are 324 possible patterns, and 178 of them are present in the data when missing values are not considered.

respond to *Environmentalist* individuals for Class A and *Neutral* individuals for Class B. Even though the composition of the classes is not strictly identical across LC models, their average composition is very comparable in all cases.

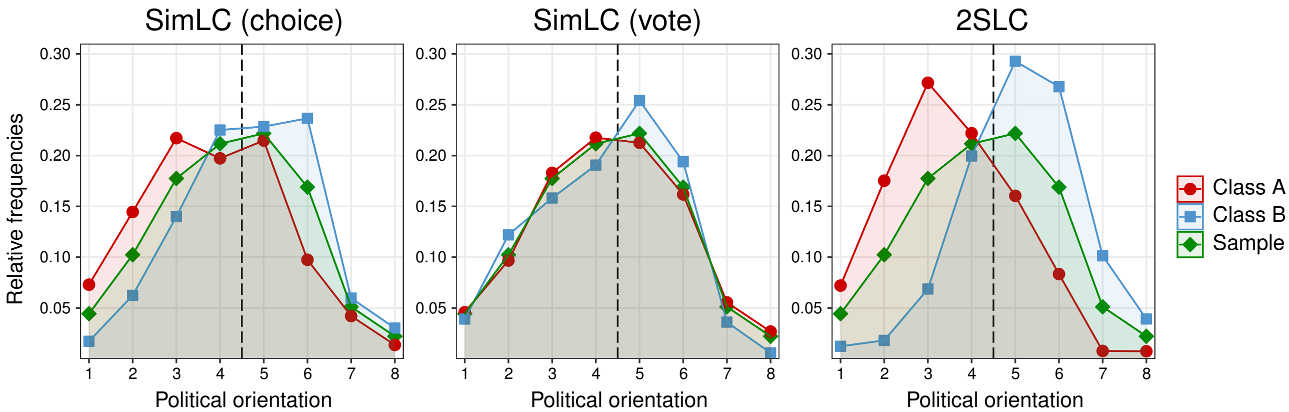
Table 7: Distribution of clustering variables

		Class A			Class B		
	Sample	Choice	Vote	2SLC	Choice	Vote	2SLC
Env. adaptation							
Not ready	11.77	8.55	11.31	2.56	14.83	13.40	22.42
Uncertain	34.30	33.94	33.03	28.86	34.65	38.72	40.59
Ready	53.92	57.51	55.66	68.59	50.53	47.89	36.99
Inability to abate							
No	48.29	55.23	50.72	63.52	41.72	39.87	30.70
Unsure	36.18	32.86	34.17	24.84	39.32	43.18	49.28
Yes	15.53	11.91	15.12	11.64	18.95	16.96	20.02
Trust in scientists							
Low	14.68	10.46	14.18	5.52	18.67	16.40	25.25
Medium	24.74	22.12	22.93	16.34	27.23	31.06	34.46
High	55.63	63.06	58.99	73.48	48.60	43.97	35.01
Eff. of carbon tax							
Never	28.16	23.71	23.28	12.89	32.37	45.13	45.79
Individuals only	3.92	3.59	4.01	2.57	4.24	3.63	5.49
Firms only	29.52	26.78	31.09	27.01	32.12	24.08	32.42
Always	38.40	45.93	41.63	57.52	31.26	27.16	16.30
Support climate strikes							
No	36.01	25.58	35.09	10.51	45.89	39.20	65.46
Unsure	31.40	30.28	29.84	30.61	32.46	36.82	32.31
Yes	32.59	44.15	35.07	58.87	21.65	23.98	2.23

Notes: Relative frequencies expressed in percentages are displayed. Frequencies of missing values are not included in the table.

Interestingly, both left and right-wing individuals are present in the two classes in all models, although members of Class A are on average more left-leaning than those of Class B, as shown in Figure 2. Political orientation is hence likely to be associated to differences in preferences regarding the environment and environmental policy, but it is not deterministic. Political conservatism is generally associated with lower concern for environmental issues, but the connection between the two might be context-specific, as argued by Nawrotzki (2012)—a point supported by our LCA. This underlines the limits of the left-versus-right linear political scale in analyzing the position of social groups regarding the environment and environmental policy, as environmentalism might reach beyond classical political divides (see Pilbeam, 2003). Segmenting society in groups with similar profiles regarding environmental perceptions and attitudes therefore requires a holistic view of the situation and should account for the specificity of the sociopolitical context.

Figure 2: Political orientation, by class



Note: 1 = extreme left, 8 = extreme right.

5.3 Analysis of choice preferences

To analyze choice data, the SimLC and 2SLC models are run and compared to a CL model and a Mixed CL model[15]. The SQ, i.e. the current CO_2 levy, is the reference; that is, the coefficients for attribute levels from the SQ are set to 0, so that estimated coefficients show the impact of non-SQ attribute levels on respondents' utilities. The tax rate is expressed as a deviation from the SQ rate (i.e. CHF 120) in hundreds of CHF. A set of dummy variables captures the effects of the allocation of proceeds, in deviation from the current situation where 67% are redistributed and 33% are dedicated to subsidies. Results are displayed in Table 8.

Based on the CL model, respondents seem to prefer proposals with a revenue allocation scheme that contains both subsidies and redistribution. Results also reveal a distaste for using subsidies for environmental assistance abroad—that is, respondents prefer emission abatement to be done within Switzerland, unlike Swedish citizens in Brännlund and Persson (2012). The SQ also seems to have some intrinsic value for respondents compared to alternatives, as shown by the significant and positive coefficient for the SQ dummy. Other attributes, including the levy rate, do not have any significant impact on the likelihood that a proposal is selected.

Results from our Mixed model are more complex to interpret, as each coefficient is interacted with individual-level characteristics in an attempt to explain the source of preference heterogeneity through covariates in addition to the random component of the parameter. Coefficients for these interactions are presented in Table A3. Results show that being female decreases the marginal utility from higher tax rates, as does right-wing political orientation, while having a tertiary level of education increases it. Political orientation is also found to exert a negative impact on the marginal utilities from the progressive redistribution of proceeds and from directing subsidies to foreign aid for the environment. Being aged between 18 and 34 however positively impacts the latter marginal utility, while living in the French-speaking region of Switzerland has a positive effect on the preference coefficient for the use of subsidies for foreign aid. Overall, although some factors seem to have impacts on their own when

[15] All model regressions have been performed with `R`'s package `apollo` (Hess and Palma, 2019).

Table 8: Results: choice preferences

	CL	Mixed		SimLC		2SLC	
		μ	σ	Class A	Class B	Class A	Class B
SQ	0.56***	0.12	2.03***	−0.34**	0.94***	−0.07	1.02***
	(0.10)	(0.62)	(0.16)	(0.14)	(0.22)	(0.16)	(0.19)
Rate	−0.09	0.71	2.05***	0.92***	−1.79***	1.26***	−1.90***
	(0.06)	(0.48)	(0.21)	(0.23)	(0.42)	(0.22)	(0.34)
Rate (squared)				−0.51***	0.53*	−0.70***	0.63***
				(0.14)	(0.31)	(0.14)	(0.24)
Redist. 100% — Sub. 0%	−0.59***	−1.06	1.37***	−0.67***	−0.69***	−0.90***	−0.29
	(0.10)	(0.75)	(0.28)	(0.15)	(0.25)	(0.16)	(0.22)
Redist. 67% — Sub. 33%	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
Redist. 33% — Sub. 67%	−0.03	−0.76	0.69*	−0.06	−0.43	−0.09	−0.12
	(0.11)	(0.64)	(0.40)	(0.14)	(0.27)	(0.15)	(0.20)
Redist. 0% — Sub. 100%	−0.35***	−1.13*	1.24***	−0.34***	−0.61***	−0.41***	−0.44**
	(0.10)	(0.62)	(0.27)	(0.13)	(0.22)	(0.14)	(0.20)
Redistribution: Uniform	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
Redistribution: Progressive	0.12	0.83	1.41***	0.45***	−0.66***	0.39***	−0.37***
	(0.07)	(0.51)	(0.19)	(0.11)	(0.19)	(0.11)	(0.14)
Subsidies: Building Program	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
Subsidies: Foreign aid	−0.58***	−0.74	1.82***	−0.37***	−1.43***	−0.53***	−0.98***
	(0.10)	(0.70)	(0.25)	(0.13)	(0.26)	(0.15)	(0.24)
Subsidies: Local initiatives	0.10	0.38	1.31***	0.35***	−0.50**	0.15	0.05
	(0.08)	(0.54)	(0.23)	(0.13)	(0.22)	(0.14)	(0.18)
Obs.	3516	3516		3516		3516	
McFadden's R^2	0.11	0.27		0.23		0.17	
AIC	6926.00	5791.59		6021.27		6481.78	
CAIC	6983.32	6364.80		6214.73		6610.75	
BIC	6975.32	6284.80		6187.73		6592.75	
Adj. BIC	6949.90	6030.60		6101.94		6535.56	

Notes: ***p-value < 0.01; **p-value < 0.05; *p-value < 0.1. 1000 MLHS (Hess et al., 2006) inter-individual draws have been generated for random parameters in the Mixed model.

taken separately, little general conclusion can be drawn from these results due to the way this model handles individual-level covariates. Random heterogeneity across respondents is important, though, given the large and significant values of most estimated standard deviations in Table 8.

While environmental orientation can be expressed in a continuum, it is likely that the individuals' positions cluster in several distinct groups. Based on this assumption, we attempt to identify a number of classes that can be interpreted as factions with relatively homogeneous preferences with regard to environmental taxation. Indeed, the LC models are much more informative regarding the source of heterogeneity than the Mixed model, as the two classes described in Section 5.2 are found to have very heterogeneous preferences regarding attribute levels. In the results from the SimLC model, only Class B (the *Neutral* group) displays strong preference for the SQ, while Class A (the *Environmentalist* group) displays a distaste for it. The proposed maximum rate of the CO_2 levy also affects each group differentially: *Environmentalists* gain in utility as the rate becomes higher, while the utility of *Neutrals* diminishes as the rate increases. This finding nuances previous conclusions from the literature on carbon taxes—that is, that people dislike high tax rates (see Carattini et al., 2018)—by underlining that this behavior corresponds only to a share of society, while there exists another share who seems to support the role of carbon taxation in fighting GHG emissions and thus prefers higher tax rates to make the policy more effective. In our model, a quadratic term is included to capture the fact that even if some respondents might prefer higher levy rates than the current one, it is likely that there exists a maximum value above which their marginal utility would nevertheless become negative. Our results seem to confirm that intuition, with a utility-maximizing rate of approximately CHF 210 for the *Environmentalists*. Interestingly, this amount happens to correspond to the maximum rate proposed in the new CO_2 law.

Results from the SimLC model also show that the absence of subsidies and redistribution lowers both classes' utilities. Their preferences nevertheless differ regarding the progressiveness of the CO_2 levy, as *Environmentalists*' utility is higher if proceeds are redistributed as an inverse function of income, while *Neutrals* prefer uniform lump-sum transfers. Both groups prefer subsidies not to be used for foreign environmental aid, with a significantly stronger aversion for *Neutrals*: a t-test for the difference between the two coefficients gives a test statistic of -3.65. *Environmentalists* also prefer proposals in which subsidies are directed toward local community initiatives, while the utility of *Neutrals* is lower when it is the case.

Results from the 2SLC model corroborate those from the SimLC, with only minor differences. *Environmentalists* are now found to be indifferent between the SQ and alternative proposals, and the use of subsidies for local community initiatives has no impact on their utility. *Neutrals* are indifferent regarding the presence or absence of subsidies and their use for local community initiatives. The fact that similar results are obtained using this two-step method supports the idea that LCs obtained using clustering variables more general than choices from the DCE captures the same general latent structure of society regarding public opinion on carbon taxation. There is therefore strong evidence for the presence of two distinct *citizen profiles* within Switzerland's population, with opposing preferences regarding the design of the CO_2 levy.

In terms of statistical performance, whether the SimLC model or the Mixed model is the most powerful is difficult to determine. Consistent AIC (CAIC, see Nylund et al., 2007) and BIC suggest the SimLC model performs better, while AIC and adjusted BIC suggest the opposite. Judging the two models on a purely statistical basis is hence not possible. We express a preference for the LC method for several reasons. First, its capacity to synthesize heterogeneity in an easily understandable factor—the latent classes—make it more useful to analyze how preferences differ within a population. The high degree of separation of the two classes also supports the idea that preferences tend to cluster in homogeneous groups instead of continuously differing across respondents. On the other hand, the Mixed model is difficult to interpret regarding its handling of covariates, and it relies on unverifiable and arbitrary distributional assumptions for the random component of the parameters. A modeling strategy based on distinct classes is thus favored, also because it does not impose any restrictive distribution assumption on preference heterogeneity or any restriction on their possible correlation with other unobserved factors captured by the model's residuals.

Overall, LC models are more informative than the CL and the Mixed models because they underline how the observed heterogeneity in the sample impacts preferences and responses. *Environmentalists* have a preference for higher carbon tax rates, a redistribution of proceeds that benefits low-income households and for using part of the proceeds for environmental subsidies, while *Neutrals* prefer to stick with the SQ, as they favors low tax rates and uniform lump-sum redistribution. In absence of any form of clustering, these important differences would remain unnoticed. Integrating covariates using a latent variable thus appears more meaningful than simple interaction terms.

5.4 Analysis of voting preferences

Analyzing data from the hypothetical votes is less straightforward to conceptualize than for the choice data. Given their nature, what we test for here is the impact of each alternative's attributes on its probability of being voted *Yes* by a respondent, conditional on having been selected as the preferred alternative in a choice task[16]. We are thus looking at the transition from *being preferred to other proposals* to *being supported in a referendum*, that is, from relative (passive) preference—i.e. acceptance—to active support. Note that the model is binary, as the *No* and *Abstain* options have been merged to form the reference category of non-support[17]. Regression results are shown in Table 9.

The CL model provides few significant results: the absence of subsidies or their use for foreign environmental aid both lower support, while the progressive redistribution of proceeds seems to increase it—although the latter relation is only weakly significant. The Mixed model does not provide much more information: the sole meaningful result lies in the large heterogeneity across respondents, as revealed by the values of estimated standard deviations. Coefficients for covariates presented in Table A4 are not very informative either.

From the SimLC model, it appears that the impact of the progressive redistribution of proceeds is not significant for any of the two groups, and the use of tax proceeds to finance foreign environmental aid has a significant negative impact for *Environmentalists* only. The most interesting result is that *Environmentalists* have a higher propensity to vote *Yes* than *Neutrals*—everything else being equal—as shown by the significant positive coefficient for the constant for *Environmentalists* and the large negative constant for *Neutrals*. The significant positive constant for *Environmentalists* is also found with the 2SLC model, but the constant for *Neutrals* is however close to 0 in this case. The absence of subsidies or their use for foreign environmental aid lower the propensity of *Environmentalists* to vote *Yes*, as is an increase in the tax rate for *Neutrals*. Redistributing proceeds as an inverse function of income also increases the probability that *Environmentalists* vote *Yes* in a referendum. Overall, *Environmentalists* display global support for the CO_2 levy; *Neutrals* seem however not to support it, or at least to be indifferent or undecided.

In terms of statistical performance, the Mixed model is less powerful than the two LC models, which supports our prior that heterogeneity tends to be clustered rather than continuously distributed across

[16]This means that hypothetical votes on the current CO_2 levy of respondents who never chose the SQ in the choice tasks have been removed from the sample. Otherwise, the meaning of results would lack consistency.

[17]Results do not significantly differ if a MNL model with all three options are considered instead and separate coefficients are estimated for each. The binary CL model is preferred for parsimony and readability reasons.

Table 9: Results: vote preferences

	CL	Mixed		SimLC		2SLC	
		μ	σ	Class A	Class B	Class A	Class B
Cons.	0.45***	0.82	2.27***	1.25***	−4.82*	0.81***	0.11
	(0.09)	(0.69)	(0.47)	(0.15)	(2.53)	(0.15)	(0.15)
Rate	0.04	0.24	1.20*	−0.53	0.02	0.50	−1.31***
	(0.10)	(0.97)	(0.62)	(0.37)	(1.20)	(0.46)	(0.50)
Rate (squared)				0.28	0.82	−0.26	0.70*
				(0.27)	(0.89)	(0.32)	(0.37)
Redist. 100% — Sub. 0%	−0.64***	−2.54	1.15	−0.75***	−7.44***	−1.14***	−0.29
	(0.18)	(1.72)	(1.03)	(0.23)	(2.43)	(0.31)	(0.27)
Redist. 67% — Sub. 33%	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
Redist. 33% — Sub. 67%	−0.11	−0.29	0.07	−0.15	−0.04	−0.33	0.05
	(0.19)	(1.77)	(0.49)	(0.24)	(0.65)	(0.31)	(0.29)
Redist. 0% — Sub. 100%	−0.25	0.35	3.69**	−0.09	−2.01**	−0.23	−0.48*
	(0.16)	(1.86)	(1.75)	(0.23)	(0.89)	(0.26)	(0.29)
Redistribution: Uniform	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
Redistribution: Progressive	0.27*	1.63	2.71**	0.29	0.31	0.64***	−0.19
	(0.14)	(1.44)	(1.10)	(0.19)	(0.63)	(0.23)	(0.24)
Subsidies: Building Program	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
Subsidies: Foreign aid	−0.42**	0.80	2.70**	−0.72***	3.59	−0.54**	−0.49
	(0.18)	(2.05)	(1.33)	(0.25)	(2.56)	(0.26)	(0.37)
Subsidies: Local initiatives	−0.08	0.45	2.79***	−0.39*	3.87	0.02	−0.11
	(0.14)	(1.33)	(1.07)	(0.20)	(2.50)	(0.25)	(0.22)
Obs.	1645	1645		1645		1645	
McFadden's R^2	0.03	0.12		0.10		0.06	
AIC	2235.64	2158.10		2115.78		2185.14	
CAIC	2286.88	2670.54		2288.73		2300.44	
BIC	2278.88	2590.54		2261.73		2282.44	
Adj. BIC	2253.47	2336.39		2175.95		2225.25	

Notes: ***p-value < 0.01; **p-value < 0.05; *p-value < 0.1. 1000 MLHS (Hess et al., 2006) inter-individual draws have been generated for random parameters in the Mixed model.

respondents. Our preference for latent classes is again confirmed in this case, although their capacity to explain differences in voting behaviors is not very strong.

6 Conclusion

Carbon taxation is an important instrument used by governments trying to implement an energy transition. Public opinion, however, is not always favorable and the literature demonstrates wide individual heterogeneity in this domain. DCE is a powerful tool to identify various sources of heterogeneity as well as moderating effects in valuation of policy attributes. We illustrate the extent of individual heterogeneity and how to adequately model it with several econometric methods using an application to the debate on the 2020 Swiss CO_2 levy reform. Focusing on measures of acceptance and support, we implement two choice experiments in an online survey answered by 586 respondents. The first experiment, aimed at measuring acceptance, is based on preferences between randomly assigned taxation schemes, while the second focuses on a support measure through a hypothetical voting exercise. Overall, our results favor LC models that can classify the individuals into distinctive clusters with relatively homogeneous preferences.

We identify two classes of respondents, which can be described as roughly corresponding to *Environmentalist* and *Neutral* citizen profiles, given their respective patterns of perceptions and attitudes toward the environment. While showing contrasting policy preferences with regard to key attributes of a carbon tax, this grouping goes beyond the usual left-right political divisions. Explaining the origin of this heterogeneity through the variables included in the LCA estimation procedure helps to understand the ideological structure of public opinion and the social context surrounding its expression. Accounting for such factors is crucial to analyze and characterize preferences for environmental policy attributes, and we recommend that future studies in this area pay a more systematic attention to it.

The results from our LC models have substantial policy implications, in that gaining support from one social group might cost support from another. This finding highlights the diversity of environmental preferences and their inherent oppositions, an important aspect of political acceptance in a democratic context, which could be overlooked with less sophisticated models. While our acceptance experiment identifies two clearly defined preference groups, the hypothetical voting exercise is less conclusive, calling for further research on differences between acceptance and active support with respect to carbon taxes. In particular, preference formation processes (see Druckman and Lupia, 2000) should be investigated further in the context of environmental policy, so that support and resistance to carbon taxes are better understood.

From a policy perspective, our findings point to two important conclusions for Switzerland and, by extension, to other countries. First, given that the optimal tax rate diverges between the two identified groups, increasing the current rate, as is planned by the federal parliament, might not receive support from a majority of the population. Second, the extent of the presence of environmentalism in the political arena, beyond left-right divisions, should not be underestimated. The diversity of preferences should be taken into account when designing carbon taxation instruments, as populations in countries with different political cultures and preferences might respond differently to a similar policy proposal.

References

Aklin, M., Bayer, P., Harish, S. P., and Urpelainen, J. (2013). Understanding environmental policy preferences: New evidence from Brazil. *Ecological Economics*, 94:28–36.

Amdur, D., Rabe, B. G., and Borick, C. P. (2014). Public Views on a Carbon Tax Depend on the Proposed Use of Revenue. SSRN Scholarly Paper 13, Social Science Research Network, Rochester, NY.

Bakaki, Z. and Bernauer, T. (2018). Do economic conditions affect public support for environmental policy? *Journal of Cleaner Production*, 195:66–78.

Baranzini, A. and Carattini, S. (2017). Effectiveness, earmarking and labeling: Testing the acceptability of carbon taxes with survey data. *Environmental Economics and Policy Studies*, 19(1):197–227.

Beiser-McGrath, L. F. and Bernauer, T. (2019). Could revenue recycling make effective carbon taxation politically feasible? *Science Advances*, 5(9):eaax3323.

Blasch, J. and Farsi, M. (2014). Context effects and heterogeneity in voluntary carbon offsetting – a choice experiment in Switzerland. *Journal of Environmental Economics and Policy*, 3(1):1–24.

Brännlund, R. and Persson, L. (2012). To tax, or not to tax: Preferences for climate policy attributes. *Climate Policy*, 12(6):704–721.

Burger, P., Schubert, I., Van Dijk, J., Puntiroli, M., Volland, B., Weber, S., and Farsi, M. (2018). Consommation d'énergie des ménages en Suisse : Principaux résultats de l'enquête sur la consommation énergétique des ménages. Technical report.

Carattini, S., Baranzini, A., Thalmann, P., Varone, F., and Vöhringer, F. (2017). Green Taxes in a Post-Paris World: Are Millions of Nays Inevitable? *Environmental and Resource Economics*, 68(1):97–128.

Carattini, S., Carvalho, M., and Fankhauser, S. (2018). Overcoming public resistance to carbon taxes. *Wiley Interdisciplinary Reviews: Climate Change*, 9(5):e531.

Cruz, S. M. (2017). The relationships of political ideology and party affiliation with environmental concern: A meta-analysis. *Journal of Environmental Psychology*, 53:81–91.

Drews, S. and van den Bergh, J. C. J. M. (2016). What explains public support for climate policies? A review of empirical and experimental studies. *Climate Policy*, 16(7):855–876.

Dreyer, S. J. and Walker, I. (2013). Acceptance and Support of the Australian Carbon Policy. *Social Justice Research*, 26(3):343–362.

Druckman, J. N. and Lupia, A. (2000). Preference Formation. *Annual Review of Political Science*, 3(1):1–24.

Dunlap, R. E. (1975). The Impact of Political Orientation On Environmental Attitudes and Actions. *Environment and Behavior*, 7(4):428–454.

Dunlap, R. E. (1989). Public Opinion and Environmental Policy. In Lester, J. P., editor, *Environemntal Politics and Policy: Theories and Evidence*, page 406. Duke University Press, Durham, 1st edition.

Ercolano, S., Gaeta, G. L., and Romano, O. (2014). Environmental tax reform and individual preferences: An empirical analysis on European micro data. *Journal of Behavioral and Experimental Economics*, 51:1–11.

Fernandez, R. and Rodrik, D. (1991). Resistance to Reform: Status Quo Bias in the Presence of Individual- Specific Uncertainty. *The American Economic Review*, 81(5):1146–1155.

Gevrek, Z. E. and Uyduranoglu, A. (2015). Public preferences for carbon tax attributes. *Ecological Economics*, 118:186–197.

Goulder, L. H. (1995). Environmental taxation and the double dividend: A reader's guide. *International Tax and Public Finance*, 2(2):157–183.

Greene, W. H. and Hensher, D. A. (2003). A latent class model for discrete choice analysis: Contrasts with mixed logit. *Transportation Research Part B: Methodological*, 37(8):681–698.

Hammar, H. and Jagers, S. C. (2006). Can trust in politicians explain individuals' support for climate policy? The case of CO2 tax. *Climate Policy*, 5(6):613–625.

Harring, N. and Jagers, S. C. (2013). Should we trust in values? Explaining public support for pro-environmental taxes. *Sustainability*, 5(1):210–227.

Hensher, D. A. and Greene, W. H. (2003). The Mixed Logit model: The state of practice. *Transportation*, 30(2):133–176.

Hess, S. and Palma, D. (2019). Apollo: A flexible, powerful and customisable freeware package for choice model estimation and application. *Journal of Choice Modelling*, 21:100170.

Hess, S., Train, K. E., and Polak, J. W. (2006). On the use of a Modified Latin Hypercube Sampling (MLHS) method in the estimation of a Mixed Logit Model for vehicle choice. *Transportation Research Part B: Methodological*, 40(2):147–163.

Hoffman, S. D. and Duncan, G. J. (1988). Multinomial and conditional logit discrete-choice models in demography. *Demography*, 25(3):415–427.

Hsu, S.-L., Walters, J., and Purgas, A. (2008). Pollution tax heuristics: An empirical study of willingness to pay higher gasoline taxes. *Energy Policy*, 36(9):3612–3619.

Kallbekken, S. and Sælen, H. (2011). Public acceptance for environmental taxes: Self-interest, environmental and distributional concerns. *Energy Policy*, 39(5):2966–2973.

Leiserowitz, A. (2006). Climate Change Risk Perception and Policy Preferences: The Role of Affect, Imagery, and Values. *Climatic Change*, 77(1):45–72.

Linzer, D. A. and Lewis, J. B. (2011). poLCA: An R package for polytomous variable latent class analysis. *Journal of statistical software*, 42(10):1–29.

Manski, C. F. (1977). The structure of random utility models. *Theory and Decision*, 8(3):229–254.

Masyn, K. E. (2013). Latent Class Analysis and Finite Mixture Modeling. In Little, T. D., editor, *The Oxford Handbook of Quantitative Methods, Volume 2*. Oxford University Press, Oxford.

McCutcheon, A. L. (1987). *Latent Class Analysis*. Sage Publications, Inc., Newbury Park.

McFadden, D. (1974a). Conditional logit analysis of qualitative choice behavior. In Zarembka, P., editor, *Frontiers in Econometrics*, pages 105–142. Academic Press, New York.

McFadden, D. (1974b). The measurement of urban travel demand. *Journal of Public Economics*, 3(4):303–328.

McFadden, D. (1986). The Choice Theory Approach to Market Research. *Marketing Science*, 5(4):275–297.

McFadden, D. and Train, K. (2000). Mixed MNL models for discrete response. *Journal of Applied Econometrics*, 15(5):447–470.

Morey, E., Thacher, J., and Breffle, W. (2006). Using Angler Characteristics and Attitudinal Data to Identify Environmental Preference Classes: A Latent-Class Model. *Environmental and Resource Economics*, 34(1):91–115.

Murray, B. and Rivers, N. (2015). British Columbia's revenue-neutral carbon tax: A review of the latest "grand experiment" in environmental policy. *Energy Policy*, 86:674–683.

Nawrotzki, R. J. (2012). The politics of environmental concern: A cross-national analysis. *Organization & environment*, 25(3):286–307.

Nylund, K. L., Asparouhov, T., and Muthén, B. O. (2007). Deciding on the Number of Classes in Latent Class Analysis and Growth Mixture Modeling: A Monte Carlo Simulation Study. *Structural Equation Modeling: A Multidisciplinary Journal*, 14(4):535–569.

Patunru, A. A., Braden, J. B., and Chattopadhyay, S. (2007). Who Cares about Environmental Stigmas and Does It Matter? A Latent Segmentation Analysis of Stated Preferences for Real Estate. *American Journal of Agricultural Economics*, 89(3):712–726.

Pilbeam, B. (2003). Natural Allies? Mapping the Relationship between Conservatism and Environmentalism. *Political Studies*, 51(3):490–508.

Ramaswamy, V., Desarbo, W. S., Reibstein, D. J., and Robinson, W. T. (1993). An Empirical Pooling Approach for Estimating Marketing Mix Elasticities with PIMS Data. *Marketing Science*, 12(1):103–124.

Rhead, R., Elliot, M., and Upham, P. (2018). Using latent class analysis to produce a typology of environmental concern in the UK. *Social Science Research*, 74:210–222.

Ricke, K., Drouet, L., Caldeira, K., and Tavoni, M. (2018). Country-level social cost of carbon. *Nature Climate Change*, 8(10):895–900.

Rotaris, L. and Danielis, R. (2019). The willingness to pay for a carbon tax in Italy. *Transportation Research Part D: Transport and Environment*, 67:659–673.

Sælen, H. and Kallbekken, S. (2011). A choice experiment on fuel taxation and earmarking in Norway. *Ecological Economics*, 70(11):2181–2190.

Samuelson, W. and Zeckhauser, R. (1988). Status quo bias in decision making. *Journal of Risk and Uncertainty*, 1(1):7–59.

Schumacher, I. (2014). An Empirical Study of the Determinants of Green Party Voting. *Ecological Economics*, 105:306–318.

Sclove, S. L. (1987). Application of model-selection criteria to some problems in multivariate analysis. *Psychometrika*, 52(3).

Swenson, M. R. and Wells, W. D. (1997). Useful Correlates of Pro-Environmental Behavior. In Goldberg, M. E., Fishbein, M., and Middlestadt, S. E., editors, *Social Marketing: Theoretical and Practical Perspectives*, page 457. Lawrence Erlbaum associates, Inc., Mahwah, NJ.

Tein, J.-Y., Coxe, S., and Cham, H. (2013). Statistical Power to Detect the Correct Number of Classes in Latent Profile Analysis. *Structural Equation Modeling: A Multidisciplinary Journal*, 20(4):640–657.

Thalmann, P. (2004). The public acceptance of green taxes: 2 million voters express their opinion. *Public Choice*, 119(1-2):179–217.

Torgler, B. and García-Valiñas, M. A. (2007). The determinants of individuals' attitudes towards preventing environmental damage. *Ecological Economics*, 63(2):536–552.

Valeri, E., Gatta, V., Teobaldelli, D., Polidori, P., Barratt, B., Fuzzi, S., Kazepov, Y., Sergi, V., Williams, M., and Maione, M. (2016). Modelling individual preferences for environmental policy drivers: Empirical evidence of Italian lifestyle changes using a latent class approach. *Environmental Science & Policy*, 65:65–74.

Van Liere, K. D. and Dunlap, R. E. (1980). The Social Bases of Environmental Concern: A Review of Hypotheses, Explanations and Empirical Evidence. *Public Opinion Quarterly*, 44(2):181–197.

Wan, C., Shen, G. Q., and Choi, S. (2017). A review on political factors influencing public support for urban environmental policy. *Environmental Science & Policy*, 75:70–80.

Weber, S., Burger, P., Farsi, M., Martinez-Cruz, A., Puntiroli, M., Schubert, I., and Volland, B. (2017). Swiss Household Energy Demand Survey (SHEDS): Objectives, Design, and Implementation.

Wolsink, M. (2010). Contested environmental policy infrastructure: Socio-political acceptance of renewable energy, water, and waste facilities. *Environmental Impact Assessment Review*, 30(5):302–311.

Wolsink, M. (2018). Social acceptance revisited: Gaps, questionable trends, and an auspicious perspective. *Energy Research & Social Science*, 46:287–295.

World Bank (2019). Using Carbon Revenues. Technical Report 16, World Bank, Washington, DC.

Wüstenhagen, R., Wolsink, M., and Bürer, M. J. (2007). Social acceptance of renewable energy innovation: An introduction to the concept. *Energy Policy*, 35(5):2683–2691.

Ziegler, A. (2017). Political orientation, environmental values, and climate change beliefs and attitudes: An empirical cross country analysis. *Energy Economics*, 63:144–153.

Appendix

Table A1: Variables used in LCA

Exogenous covariates	Scale	Description
Socioeconomic		
Female	Binary	The respondent is female.
Age	Categorical	Age group of the respondent (18-34, 35-54, 55+).
Tertiary edu.	Binary	The respondent has a tertiary level of education.
Geographic		
Residential env.	Categorical	The type of area in which the respondent lives (city, agglomeration, countryside).
Romandie	Binary	The respondent lives in the French-speaking part of Switzerland.
Political		
Pol. orientation	1–8	The respondent's self-placement on a left-right political scale (far left–far right).
Clustering variables		
Env. adaptation	1–3	The respondent claims she is ready to take steps to adopt environmentally friendly behaviors even if it causes daily inconveniences (not ready–uncertain–ready).
Inability to abate	1–3	The respondent agrees that she cannot do much to lower her CO_12 emissions (no–unsure–yes).
Trust in scientists	1–3	The respondent's level of trust for information from scientists on energy and energy-saving (low–medium–high).
Eff. of carbon tax	Categorical	The respondent believes that taxing CO_2 emissions is effective to push individuals and firms to lower their CO_2 emissions (never–individuals only–firms only–always).
Support climate strikes	1–3	The respondent supports the *School strike for climate* movement (no–unsure–yes).

Table A2: Descriptive statistics

		SimLC (choice)		SimLC (vote)		2SLC		
	Sample	Class A	Class B	Class A	Class B	Class A	Class B	Switzerland
N	586							
Class size		48.65	51.35	77.67	22.33	53.6	46.4	
Gender: female	48.46	51.33	45.75	47.17	52.97	54.72	41.23	50.79
Age								
18-34	21.84	26.65	17.29	19.89	28.63	24.83	18.39	25.64
35-54	40.96	44.01	38.06	42.22	36.55	42.71	38.93	35.13
55+	37.2	29.34	44.65	37.89	34.82	32.46	42.68	39.23
Tertiary edu.	48.12	49.29	47.02	51.08	37.83	54.92	40.26	31.14
Residential env.								
City	50.68	54.57	47.00	51.99	46.14	58.97	41.11	62.89
Agglomeration	28.16	24.72	31.41	28.79	25.96	22.44	34.76	21.34
Countryside	21.16	20.71	21.58	19.22	27.90	18.58	24.14	15.77
Romandie	23.55	24.52	22.63	23.33	24.33	26.52	20.11	25.34
Swiss nationality	91.98	91.53	92.40	91.06	95.16	90.25	93.97	75.18

Notes: Relative frequencies expressed in percentages are displayed. For Switzerland, frequencies of gender, age groups and nationality are displayed for residents aged above 18 in 2018; residential environment and Romandie for residents aged above 15 in 2018; tertiary education for residents aged above 18 in 2017.

Table A3: Mixed logit covariates: choice preferences

	SQ	Rate	Red. 100% Sub. 0%	Red. 33% Sub. 66%	Red. 0% Sub. 100%	Red.: Prog.	Sub.: F.A.	Sub.: Local in.
Female	−0.21	−0.57**	−0.17	0.11	0.27	−0.13	0.11	0.55*
	(0.32)	(0.24)	(0.36)	(0.33)	(0.31)	(0.25)	(0.34)	(0.28)
Age: 18-34	−0.16	−0.11	−0.14	0.18	0.01	0.17	0.84**	0.39
	(0.41)	(0.31)	(0.47)	(0.39)	(0.40)	(0.32)	(0.43)	(0.37)
Age: 55+	0.31	−0.27	−0.20	0.16	0.20	−0.31	−0.49	−0.28
	(0.35)	(0.27)	(0.41)	(0.38)	(0.35)	(0.29)	(0.41)	(0.32)
Tertiary edu.	−0.12	0.56**	−0.59	0.24	−0.27	−0.08	−0.56	−0.33
	(0.31)	(0.24)	(0.37)	(0.32)	(0.31)	(0.25)	(0.35)	(0.28)
City	0.05	0.51*	−0.05	0.61	0.14	0.15	0.55	0.05
	(0.39)	(0.28)	(0.45)	(0.39)	(0.38)	(0.30)	(0.44)	(0.34)
Countryside	−0.21	0.05	−0.47	−0.07	0.07	0.63*	0.44	0.05
	(0.46)	(0.31)	(0.54)	(0.47)	(0.44)	(0.36)	(0.51)	(0.42)
Romandie	0.57	−0.27	0.11	0.64*	0.56	0.17	−0.03	0.73**
	(0.36)	(0.26)	(0.40)	(0.37)	(0.34)	(0.28)	(0.42)	(0.30)
Pol. orientation	0.07	−0.35***	0.06	0.00	−0.02	−0.24***	−0.21**	−0.16*
	(0.09)	(0.08)	(0.11)	(0.10)	(0.09)	(0.08)	(0.11)	(0.09)

Notes: ***p-value < 0.01; **p-value < 0.05; *p-value < 0.1.

Table A4: Mixed logit covariates: vote preferences

	Cons.	Rate	Red. 100% Sub. 0%	Red. 33% Sub. 66%	Red. 0% Sub. 100%	Red.: Prog.	Sub.: F.A.	Sub.: Local in.
Female	0.02	−0.04	0.35	0.14	−1.22	−0.55	−0.70	−0.11
	(0.33)	(0.49)	(0.75)	(0.83)	(0.97)	(0.72)	(1.05)	(0.75)
Age: 18-34	−1.11**	0.03	−0.65	−0.23	−1.51	1.44	2.11*	1.84*
	(0.45)	(0.63)	(0.97)	(0.94)	(1.29)	(1.01)	(1.20)	(1.07)
Age: 55+	0.22	0.71	−1.77*	−0.89	−1.52	−0.40	0.22	1.01
	(0.37)	(0.58)	(0.91)	(0.92)	(1.09)	(0.80)	(1.17)	(0.88)
Tertiary edu.	0.32	0.35	−0.04	0.37	0.10	−0.16	1.38	0.06
	(0.33)	(0.50)	(0.77)	(0.81)	(0.99)	(0.71)	(1.05)	(0.73)
City	0.02	−0.24	−0.72	0.23	1.58	−0.41	−2.04	−0.05
	(0.38)	(0.61)	(0.84)	(0.93)	(1.19)	(0.84)	(1.38)	(0.92)
Countryside	−0.72	−1.07	0.79	1.39	0.76	−0.55	−1.03	0.28
	(0.46)	(0.80)	(1.13)	(1.22)	(1.29)	(0.97)	(1.62)	(1.09)
Romandie	0.13	−0.22	0.16	1.22	0.07	−0.06	−1.35	−0.23
	(0.38)	(0.55)	(0.86)	(1.01)	(0.98)	(0.90)	(1.20)	(0.86)
Pol. orientation	0.03	−0.14	0.50**	−0.08	−0.09	−0.13	−0.20	−0.24
	(0.10)	(0.15)	(0.25)	(0.26)	(0.30)	(0.21)	(0.33)	(0.22)

Notes: ***p-value < 0.01; **p-value < 0.05; *p-value < 0.1.