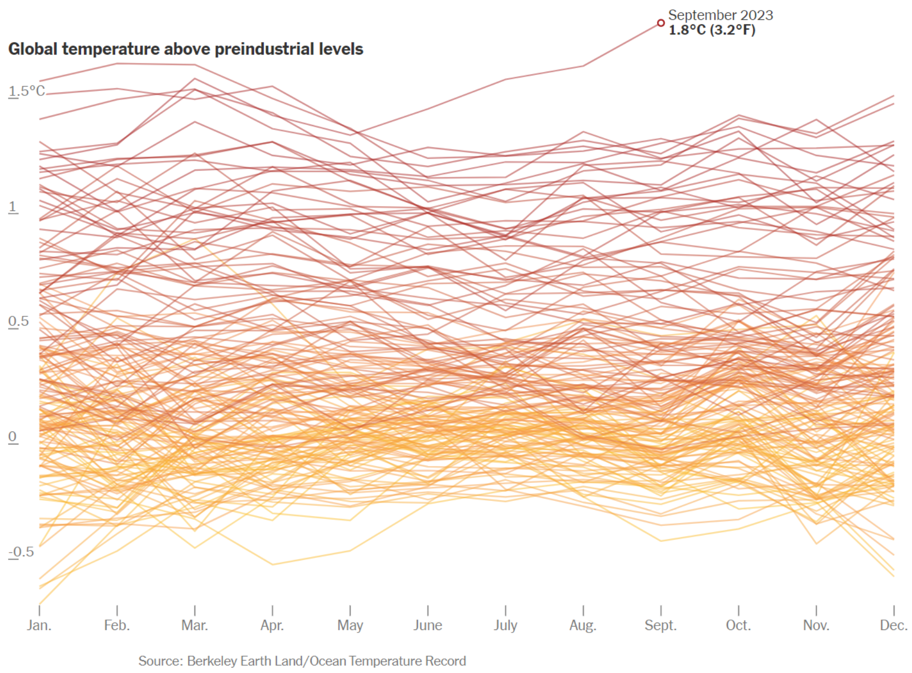

Preferred Strategies to Reduce CO2-Emissions by 30%: Insights from a Multiple Discrete-Continuous Extreme Value Model

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Abstract

While cost of climate policies and their distributional consequences have become increasingly relevant, very little is currently known about how people across societal sub-groups evaluate and trade-off necessary behavioural changes and financial costs when faced with decisions about how to reduce individual carbon emissions. To understand such preferred pathways, a priority evaluator experiment was fielded. 3‘456 participants were tasked to reduce their initial carbon emission levels by 30% by choosing their preferred strategy mix and how intensely they want to pursue any chosen strategy. We use a *Multiple Discrete-Continuous Extreme Value Model* (MDCEV) to model both dimensions simultaneously. We find that while strategies that imply behavioral change are generally accepted, they usually only contribute little to overall savings. Meanwhile, outsourcing a considerable chunk of reductions via certificates is a prominent choice. In particular, high-income households tend to reduce emissions via investments, while lower-income households may have to bear disproportionally more of the behavioral cost in order to reach the reduction target. People further to the right on the political scale reach the target less frequently and prefer measures that benefit the housing unit (better insulation of the facade and roof), or install solar panels. This might be important since right-leaning individuals are generally more critical of climate change and the need to take personal action. Incentivizing these individuals to invest in reduction strategies might therefore be pivotal.

Keywords

Carbon Emissions; Climate Change; Multiple Discrete-Continuous Extreme Value Model; MDCEV; Choice Modeling

Suggested Citation

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Contents

List of Tables

List of Figures

1 Introduction

Urgent action is needed in order to limit climate change (IPCC, 2022). Recentently the focus has increasingly shifted to the domestic political sphere to tackle climate change (Aklin and Mildenberger, 2020), where particularly the distributional dimension of climate policy has been picked up by both the electorate and politicians, and become highly salient for both elections and referenda on climate policy (Colantone *et al.*, 2024; Schaffer, 2023; Stokes, 2016).

While cost of climate policies and their distributional consequences have become increasingly relevant, very little is currently known about how people across societal sub-groups evaluate and trade-off necessary behavioural changes and financial costs when faced with decisions about how to reduce individual carbon emissions. As individual emission reductions will become inevitable, it is imperative for policymakers to better understand the feasibility of individual adaptation options to develop policy instruments that will effectively foster change, as well as provide support where such changes pose unfavorable distributional outcomes. Accordingly, this paper investigates the following: When tasked with reducing their personal carbon emissions to a level that is compatible with net-zero goals, how do people trade off behavioral adaptations and lifestyle changes?

The data was collected as part of the *Swiss Mobility Panel* (Wave 3) where a priority evaluator experiment was fielded. Individuals' initial carbon footprints were first calculated and the participants were then asked to reduce their emissions by 30%. 16 different reduction strategies were available and respondents could select a menu of strategies (intensive margin) as well as control the intensity to pursue this strategy, thereby controlling the CO_2-reduction amount (extensive margin). Both dimensions of these choices are modeled simultaneously with a *Multiple Discrete-Continuous Extreme Value Model* (MDCEV).

Therefore, we are able to identify preferences for behavioral changes, which sub-groups of respondents are more or less likely to meet their emissions reduction targets (and how), and in how far the political scale (left or right), climate perceptions and the perceived need to take (individual) action play a role in the decision-making.

2 Methodology

We first outline the data collection method and then introduce the econometric framework which is able to model both discrete and continuous choice dimensions simultaneously.

2.1 Data

The data was collected with help of a priority evaluator-based methodology: A highly individualized and interactive choice task that allows each respondent to develop a set of behavioral adaptations and mitigation pathways to reach a personalized carbon emission reduction target, similar to Jäggi (2015).

The priority evaluator (PE) was fielded in an online survey amongst a population-representative sample in Switzerland ($N = 5‘941$) in 2022. 3‘456 individuals received the PE treatment and after filtering 2‘792 individuals remained in the analytic sample that underlies this analysis. Participants rushing through the experiment or violating the task definition (e.g., increasing the carbon emissions or compensating more than 100%) were excluded.

First, respondents are asked about their CO_2-relevant behaviors and living conditions (carbon calculator). These responses are utilized to calculate each respondent's CO_2-emissions and populate a list of realistic adaptation options. The dynamic nature of the digital application then allows citizens to compare the effectiveness of these different adaptations, while at the same time, weight their choices against behavioral and financial costs. The respondents are tasked with reaching a 30% reduction target in their carbon emissions and are presented with the annual (over time) and one-time purchase costs or benefits of their changes.

In total, individuals had at most (depending on the individual-specific availabilities) 15 reduction strategies to choose from Table 1. As the 30% reduction target was not enforced, individuals were free to leave the experiment prematurely which therefore constitutes an implicit choice, namely not to compensate part of the carbon emission target.

Table 1: Emission reduction strategies.

			Availability			
Sector	Label	Strategy	All	House owners	Other	Note
Housing	ht.pmp	Install heat pump		✓		
	inslt.fcd	Insulate facade		✓		
	inslt.rf	Insulate roof		✓		
	rdc.tmp	Reduce room temparature	✓			
	rplc.wndws	Replace windows		✓		
	slr.pnls	Install solar panels		✓		
	vntltn	Install controlled ventilation		✓	✓	Available for apartment owners
Mobiltiy	lng.flghts	Reduce long-distance flights			✓	Available for flyers
	mdm.flghts	Reduce medium-distance flights			✓	Available for flyers
	rdc.nd.cmpnst	Reduce and compensate car travel			✓	Available for car owners
	rplc.r.sll	Replace or sell car			✓	Available for car owners
	shrt.flghts	Reduce short-distance flights			✓	Available for flyers
Other	co2.offset	CO2 offset	✓			Accept certificate offset if PE was prematurely ended
	crtfct	CO2 certificate			✓	Available if undercomp
	dt	Diet	✓			Change dietary preferences
	undercomp	Undercompensate	✓			Implicit choice not to reach target

2.2 Econometric framework

In this section, we introduce the *Multiple Discrete-Continuous Extreme Value Model* (MDCEV) as proposed by Bhat (2008). We use the flexible *apollo* package (Hess and Palma, 2019) in `R` (R Core Team, 2023) to maximize the simulated log-likelihood. The notation is based on the user manual (Hess and Palma, 2023). Further, the `R`-package *rmdcev* and accompanying paper (Lloyd-Smith, 2020) are useful resources to study the methodology.

The choice process involves choosing one or several alternatives from a finite set and then choosing a non-negative amount of each selected alternative. Formally, the MDCEV model is a stochastic implementation of the more general Kuhn-Tucker model specifications of classical consumer maximization. The problem can be formulated as follows (Hess and Palma, 2023):

$$\begin{aligned} \max_{x_k \forall k} \quad & U_k(x_k) = \sum_{k=1}^{K} \frac{\gamma_k}{\alpha_k} \psi_k \left(\left(\frac{x_k}{\gamma_k} + 1 \right)^{\alpha_k} - 1 \right) \\ s.t. & \sum_{k=1}^{K} x_k p_k = B \end{aligned} \tag{1}$$

where K is the number of alternatives, x_k is the amount consumed of alternative k and p_k is the associated unit price or cost. B is the budget available for consumption. In our problem formulation, individuals derive utility from choosing among CO_2-emission reduction strategies where the outside good reflects the emission amount after being satisfied with the overall reduction. The budget is thus 100% and the unit price p_k is constant, indicating a constant marginal rate of substitution among the K alternatives.

Interpretation in brief (Lloyd-Smith, 2020):

- The ψ_k parameters represent marginal utility of consuming alternative k at the point of zero consumption (i.e., baseline marginal utility). The greater this baseline utility the more likely the individual consumes a positive amount.
- The γ_k parameters are translation parameters that allow for corner solutions (i.e., zero consumption levels) but also influence satiation. The lower the value of γ_k the greater the satiation effect and thus the less is consumed.

- The α_k parameters control the rate of diminishing marginal utility. If $\alpha_k = 1$ then there is no satiation effect (i.e., constant marginal utility).

To conform with the random utility framework, a random error term is introduced in the baseline utility as:

$$\psi_k = \exp(V_k + \varepsilon_k) \tag{2}$$

where ε_k is an independent and identically distributed random disturbance following a *Gumbel*$(0, \sigma)$ distribution.

The modeler now has to parameterize each alternative's base utility V_k. Again, this is then the parameterized marginal utility at zero consumption and has thus nothing directly to do with the amount being consumed. Indirectly it does, however, since ceteris paribus (in particular same satiation) more is consumed the larger ψ_k.

The probability of observing the optimal consumption bundle can then be expressed in closed form as:

$$\begin{aligned} &P(x_1^*, x_2^*, \ldots, x_M^*, 0, \ldots, 0) \\ =&\frac{1}{\sigma^{M-1}} \left(\prod_{m=1}^{M} f_m \right) \left(\sum_{m=1}^{M} \frac{p_m}{f_m} \right) \left(\frac{\prod_{m=1}^{M} e^{V_m/\sigma}}{(\sum_{k=1}^{K} e^{W_k/\sigma})^M} \right) (M-1)! \end{aligned} \tag{3}$$

where $f_m = \frac{1-\alpha_m}{x_m^* + \gamma_m}$ and $W_k = V_k + (\alpha_k - 1)\log(\frac{x_k^*}{\gamma_k + 1} - \log(p_k)$, and x_k^* is the observed (optimal) consumption of alternative k.

It is well recognized that the overall utility specification Eq. (1) suffers from identification concerns as both α and γ capture satiation (Bhat, 2008). There exist four common specifications (referred to as profiles) that avoid identification issues (see e.g., Lloyd-Smith, 2020). The different profiles should be tested and the most suitable identified based on goodness of fit considerations which was done in this work.

The final model was estimated on ETH Zurich's *Euler* supercluster on ten cores (with one GB memory each) and took 02:12:25 days:hours:minutes to converge.

2.3 Model building strategy

The following steps were pursued to arrive at the final model specification:

1. Intercept-only model with individuel-specific availabilities.
2. Identifying the gamma-profile as the best-fitting amongst the three alternative profiles (*Model 1*).
3. Adding all covariates (*Model 2*).
4. Excluding all covariates with associated p-values below the 5% significance level (*Model 3*).
5. Testing the combination of factor levels (e.g., only considering the mandatory education level against the higher two education levels combined versus separately). No better-performing model according to conventional fit indicators was found.
6. Modeling Likert-style indicators via latent variables allowing for measurement errors (*Model 4*).

The last step introduces additional error components, thus yielding a multi-dimensional integral in Eq. (3), and therefore requires *Monte Carlo* simulation to evaluate the combined likelihood. 1‘000 *Sobol* draws were used for each of the six latent variables. The probability of observing a given indicator was modeled according to an ordered logit specification with no explanatory variables (i.e., at this point we only account for the measurement error).

In each step, several goodness of fit indicators (log-likelihood, AIC, and BIC) were used to identify better model fit. These are presented in table Table 2. It should be noted that the log-likelihood did not improve substantially when comparing *Model 1* to *Model 3* (The likelihood of *Model 4* is not directly comparable as it features a hybrid choice structure). This could either indicate that we miss covariates with a strong signal or that the experimental setting simply yields noisy data. A similar finding was already made by Jäggi (2015). However, a likelihood ratio test rejects the null hypothesis that the parsimonious, or restricted, model is the true model. Further, the ratio of *Number of respondents* to *Number of parameters* for *Model 4* seems critical. However, we compared the shared parameters with *Model 3* and they are stable.

Table 2: Model comparison.

	Model 1	Model 2	Model 3	Model 4
Number of respondents	2792.00	2792.00	2792.00	2792.00
Number of parameters	32.00	331.00	151.00	260.00
LL(final)	-42513.31	-41514.39	-41605.24	-71919.75
AIC	85090.62	83690.79	83512.47	144359.50
BIC	85280.52	85655.11	84408.58	145902.48

3 Results and discussion

We first illustrate overall behavior with a descriptive analysis not differentiating any sociodemographic attributes. The model then can explain choice behavior more nuanced by controlling for various explanatory factors as well as quantifying (relative) effect size.

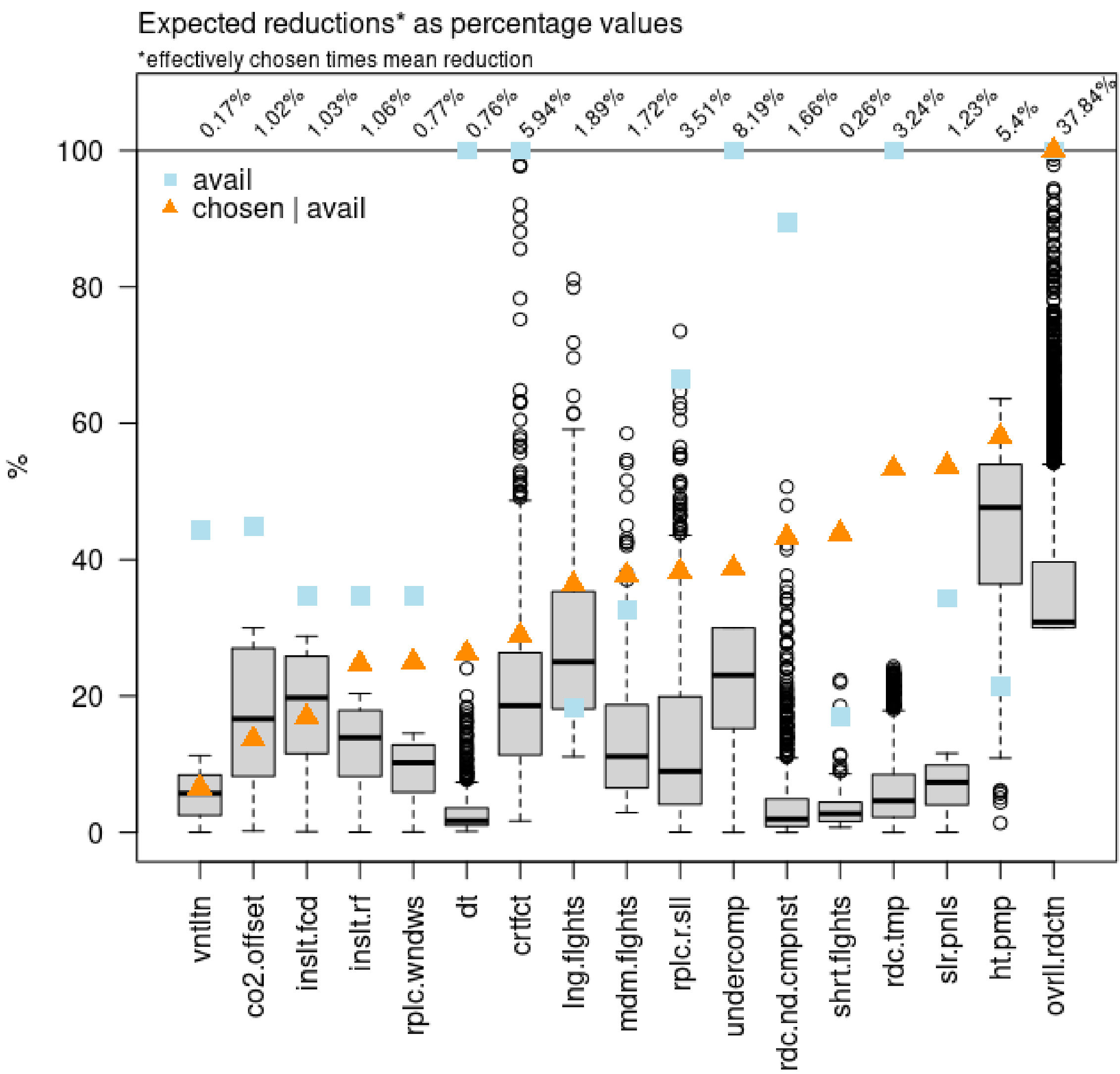
3.1 Descriptive results

Fig. 1 shows the availability proportion, the conditional choice proportion (intensive margin), and the CO_2-emission reduction (extensive margin as boxplot). Resulting expected reductions (*P(available)*P(chosen | available)*mean reduction*) are also spelled out at the top. The x-axis is ordered according to the intensive margin.

Housing-related reduction strategies are sparsely available (as these strategies are reserved for house/apartment owners, see also Table 1). Meanwhile, there seems to be a preference for heat pump and solar panels relative to more structural adjustments such as insulating the facade/roof or replacing windows. Installing controlled ventilation is the least often chosen.

There is no obvious correlation between the intensive and extensive margin. Meaning, that the strategies that have the potential to reduce a lot of CO_2 are not necessarily the most frequently chosen. People rather prefer a strategy mix. Behavioral strategies (i.e., strategies that require behavioral change) are frequently chosen but do not contribute much to overall savings. For example, reducing and compensating car travel, reducing short flights, and reducing the room temperature are often chosen but contribute only marginally to overall savings. Despite that, reducing the room temperature has a relatively big overall reduction potential due to its universal availability.

Figure 1: Extensive and intensive choice margins and resulting expected CO_2-emission reductions.



Installing a heat pump is both the most popular choice (if available) and the most effective one, with its median value close to 50%, implying that a lot of house owners could reach the reduction target by installing a heat pump with no other adjustments required. The *ovrll.rdctn* reflects the overall reduction and is centered around the reduction target. However, a little less than 50% chose to *undercompensate* (not to reach the target) with median values of around 25% (i.e., if they did not reach the target, they did so with quite a margin).

While some individuals under-compensated, some others did over-compensate. Again, the *ovrll.rdctn* boxplot illustrates that the distribution is skewed with many outliers. Some of them even compensated more than their total emissions (by buying certificates). These individuals were excluded from the analysis and are not shown in the figure. Some individuals choose to increase emissions for some strategies (for example they drive more or buy a heavier car but install a heat pump). Such cases were only few, however, but needed to be excluded from the econometric analysis as "negative" consumption (here increased CO_2-emissions) is technically not allowed.

Commenting on the effective reduction suggests that outsourcing the emission reduction by buying certificates might be an acceptable solution. Installing a heat pump and replacing or selling the car are the strategies yielding the greatest expected reduction after buying certificates. Meanwhile, simple adjustments such as reducing the room temperature have the potential to meaningfully contribute to overall emission savings because of their universal availability.

3.2 Modeling results

Before diving into the discussion of estimates, we should remember, that we essentially model utility/preference parameters. Of course, preferences can only manifest if the choice is feasible. In our model, the availabilities are exogenous (as is usually assumed) and not modeled as such. By controlling (exogenously) for individual-specific availabilities we do get unbiased estimates for preferences over the full choice set. Policymakers should keep in mind, that availability plays a role too, but is not considered in the modeling approach pursued here and the discussion that follows. For example, subsidizing heat pumps would imply a redistribution from the general population to house owners.

The estimates are presented in Table 3 along with their units and reference levels for indicator variables. Standard errors are reported in brackets. Similarly, coefficients are graphically depicted together with 95% confidence intervals in Fig. 2. Light blue dots mark the coefficients of the other strategies which helps identify whether the direction of the effect is generally shared among strategies. The reader has to keep in mind that the effect size is unit dependent: For example, for *household income* the coefficient is the marginal utility (at zero consumption) if the monthly income increases by 1‘000 Swiss francs. Therefore, if coefficients closely cluster the zero line, the table should be consulted (the units and reference levels are spelled out in the *Parameter* column).

The latent variables (LV) are also highlighted in the table. These are based on the Likert-scale indicators and are referred to as *climate perceptions* in the remainder of the text (they usually share similar tendencies regarding the direction of the effect).

Almost all variables retained in the final model are significant at least at the 5%-level and the direction of the effect seems plausible.

ASCs and gamma

The ASCs (intensive margin) do not fully align with the descriptive findings. They reflect base preferences for the average respondent given universal availability (which is counterfactual). As before, installing controlled ventilation is the least accepted strategy. Reducing the room temperature is the most accepted strategy. Choosing not to reach the target is the second most frequent choice for the average respondent. As with the descriptive results, installing a heat pump or solar panels is still the most popular housing-related investment followed by replacing the windows, insulating the facade, and installing controlled ventilation in the last place. Reducing the number of short-haul flights is more accepted than medium or long-distance flights. Buying CO_2-certificates is an accepted solution. For example, the average respondent would rather buy a certificate than waive a long-haul flight.

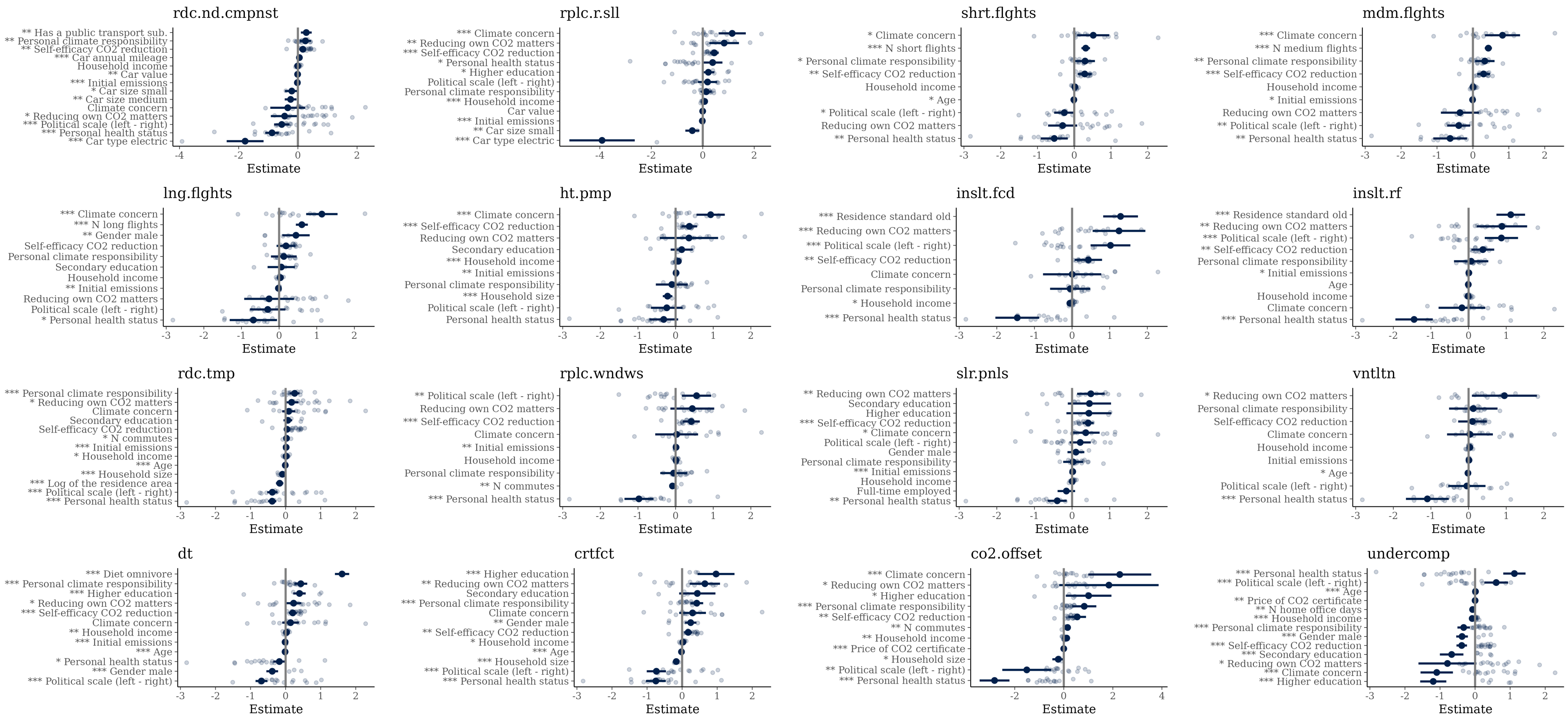
Commenting on the extensive margin (satiation, i.e., the *gamma* parameters) the descriptive findings are well-aligned: If chosen, heat pumps are the most effective measure to reduce carbon emissions by a wide margin. The second most effective strategy is to reduce long-distance flights. However, as just alluded, people are not willing to waive traveling abroad, because the utility of long-distance trips is probably large and the perceived societal benefit of not flying is rather small ("the others fly anyways"). Certificates seem pivotal for respondents to reach the target. On the other hand, the strategies that imply behavioral change are the least satiated. In particular, many respondents are willing to reduce or compensate car travel but the effective emission savings are small (even smaller than changing dietary preferences). This suggests that carbon emissions are preferably reduced with technologies rather than changes in behavior. In other words, the behavioral cost outweighs the technological cost.

Table 3: MDCEV estimation results.

	Mobility					Housing							Other			
Parameter	rdc.nd.cmpnst	rplc.r.sll	shrt.flghts	mdm.flghts	lng.flghts	ht.pmp	inslt.fcd	inslt.rf	rdc.tmp	rplc.wndws	slr.pnls	vntltn	dt	crtfct	co2.offset	undercomp
gamma	0.809*** (0.042)	3.501*** (0.218)	1.403*** (0.103)	6.406*** (0.368)	19.526*** (1.592)	40.339*** (4.545)	8.954*** (1.173)	5.493*** (0.576)	1.931*** (0.075)	5.529*** (0.482)	2.836*** (0.174)	3.867*** (0.512)	1.177*** (0.05)	11.869*** (0.578)	3.031*** (0.398)	5.89*** (0.271)
ASC	−4.501*** (0.182)	−5.076*** (0.184)	−4.711*** (0.335)	−5.611*** (0.22)	−6.042*** (0.345)	−4.622*** (0.303)	−6.33*** (0.379)	−5.641*** (0.478)	−3.157*** (0.259)	−5.465*** (0.237)	−4.799*** (0.321)	−6.712*** (0.695)	−5.556*** (0.215)	−5.152*** (0.322)	−6.27*** (0.509)	−4.336*** (0.272)
Age (years)			−0.011* (0.005)					−0.008 (0.006)	−0.01*** (0.002)			−0.017* (0.009)	−0.016*** (0.003)	−0.018*** (0.003)		0.011*** (0.003)
Car annual mileage (tsd. km/year)	0.051*** (0.007)															
Car size medium (Car size large)	−0.246** (0.102)															
Car size small (Car size large)	−0.207* (0.119)	−0.407** (0.138)														
Car type electric (Not)	−1.783*** (0.318)	−3.914*** (0.648)														
Car value (tsd. CHF)	−0.009** (0.003)	−0.004 (0.004)														
Diet omnivore (Not)													1.609*** (0.104)			
Full-time employed (Not)											−0.152 (0.119)					
Gender male (Not)					0.448** (0.186)						0.102 (0.114)		−0.382*** (0.085)	0.244** (0.084)		−0.372*** (0.085)
Has a public transport sub. (Not)	0.284** (0.093)															
Higher education (Mandatory education)		0.217* (0.12)									0.447 (0.305)		0.395*** (0.091)	0.968*** (0.269)	1.013* (0.475)	−1.193*** (0.19)
Household income (tsd. CHF/month)	−0.007 (0.012)	0.073*** (0.015)	0.016 (0.018)	0.002 (0.016)	0.034 (0.021)	0.073*** (0.019)	−0.059* (0.031)	−0.014 (0.026)	0.015* (0.009)	0.009 (0.022)	0.003 (0.015)	0.034 (0.031)	0.027** (0.011)	0.023* (0.012)	0.119** (0.04)	−0.082*** (0.014)
Household size (n)						−0.214*** (0.064)			−0.092*** (0.027)					−0.167*** (0.037)	−0.226* (0.122)	
Initial emissions (t/year)	−0.018*** (0.003)	−0.017*** (0.004)		−0.009* (0.005)	−0.019** (0.007)	0.013** (0.005)		0.008* (0.004)	0.015*** (0.002)	0.012** (0.004)	0.017*** (0.003)	0.011 (0.007)	−0.015*** (0.003)			
Log of the residence area (log sqm)									−0.17*** (0.054)							
N commutes (d/week)									0.026* (0.014)	−0.083** (0.035)					0.154** (0.062)	
N home office days (d/week)																−0.071** (0.027)
N long flights (n/year)					0.604*** (0.081)											
N medium flights (n/year)				0.43*** (0.051)												
N short flights (n/year)			0.312*** (0.059)													
Price of CO2 certificate (CHF/t)															−0.001*** (0)	0** (0)
Residence standard old (Not)							1.288*** (0.236)	1.121*** (0.194)								
Secondary education (Mandatory education)					0.057 (0.186)	0.162 (0.15)			0.062 (0.063)		0.461 (0.293)			0.433 (0.264)		−0.669*** (0.171)
Climate concern (LV)	−0.343 (0.301)	1.144*** (0.27)	0.516* (0.222)	0.824*** (0.249)	1.136*** (0.213)	0.931*** (0.192)	0.002 (0.395)	−0.176 (0.317)	0.089 (0.096)	0.028 (0.291)	0.364* (0.188)	0.037 (0.311)	0.141 (0.122)	0.298 (0.195)	2.282*** (0.655)	−1.094*** (0.236)
Personal climate responsibility (LV)	0.255** (0.097)	0.138 (0.108)	0.293* (0.137)	0.331** (0.139)	0.125 (0.175)	−0.1 (0.217)	−0.05 (0.273)	0.068 (0.233)	0.257*** (0.071)	−0.052 (0.182)	0.026 (0.134)	0.126 (0.329)	0.433*** (0.093)	0.417*** (0.094)	0.834*** (0.251)	−0.326*** (0.091)
Personal health status (LV)	−0.874*** (0.117)	0.384* (0.194)	−0.544** (0.188)	−0.634** (0.239)	−0.685* (0.321)	−0.316 (0.196)	−1.457*** (0.297)	−1.448*** (0.253)	−0.383*** (0.06)	−0.976*** (0.196)	−0.396** (0.129)	−1.095*** (0.29)	−0.179* (0.088)	−0.748*** (0.144)	−2.823*** (0.311)	1.121*** (0.162)
Political scale (left - right) (LV)	−0.546*** (0.132)	0.186 (0.191)	−0.27* (0.141)	−0.395** (0.163)	−0.303 (0.24)	−0.234 (0.214)	1.02*** (0.27)	0.872*** (0.226)	−0.38*** (0.074)	0.557** (0.199)	0.216 (0.144)	−0.046 (0.253)	−0.689*** (0.086)	−0.734*** (0.14)	−1.508** (0.51)	0.603*** (0.173)
Reducing own CO2 matters (LV)	−0.448* (0.238)	0.831** (0.294)	−0.316 (0.202)	−0.36 (0.271)	−0.267 (0.337)	0.355 (0.395)	1.247*** (0.358)	0.887** (0.341)	0.17* (0.101)	0.444 (0.297)	0.499** (0.186)	0.952* (0.441)	0.228* (0.112)	0.649** (0.22)	1.84* (1.034)	−0.788* (0.422)
Self-efficacy CO2 reduction (LV)	0.168** (0.06)	0.449*** (0.086)	0.285** (0.097)	0.296*** (0.091)	0.183 (0.128)	0.364*** (0.105)	0.433** (0.185)	0.379** (0.154)	0.04 (0.041)	0.417*** (0.115)	0.427*** (0.076)	0.105 (0.195)	0.204*** (0.058)	0.173** (0.06)	0.547** (0.184)	−0.381*** (0.076)

Note: *5%, **1%, ***0.1%; standard errors in brackets

Figure 2: Model estimates and 95% confidence intervals. Light blue dots mark the estimates of the other strategies.



Not reaching the target

Looking at the last panel (*undercomp*) of Fig. 2, the parameters are mirrored from the other strategies (light blue dots). For example, having a higher education level (compared to mandatory education only) increases the probability of reaching the target (negative effect for *undercomp*) but tends to have a positive effect on choosing any other strategy. People with bad health status, on the right of the political scale, and higher age are less likely to reach the 30% reduction target. The number of home office days, high household income, a secondary or higher education level, and being male positively contribute to reaching the target. Similarly, the (latent variables) we refer to as climate concerns all share the negative sign, implying that people with stronger concerns more often conform with the emission target.

General patterns

Some general patterns are shared among the various strategies: Individuals who use a particular strategy more intensely are more willing to save carbon via this strategy. Either because it is easier ("more behavioral leeway") or simply because the behavioral cost is smaller. For example, people driving more choose the strategy to reduce and compensate car travel more frequently. Individuals with higher initial emission levels generally favor housing-related strategies and are less willing to adjust their behavior. People with stronger stated climate perceptions (LV) tend to be more likely to accept any given strategy. On the other hand, people on the right political scale (with a few notable exceptions discussed later) are less likely to accept any given strategy.

Effects of individual variables

Subsidizing electric vehicles might be accompanied by a second-order effect: Owners of electric cars are less willing to reduce annual mileage or switch to public transport. Owners of more expensive cars (car price strongly correlates with fuel consumption and emissions) are less inclined to reduce or compensate for car travel or replace their vehicle with a more sustainable one.

Commenting on the effect of political position: The rural population tends to be politically right-leaning compared to the urban population. At the same time, the rural population is more car-dependent which probably explains the negative effect at least partially. However, accessibility metrics were tested but not found to be significant.

Public transport (PT) subscription owners are more likely to reduce or further compensate car travel, probably because they are used to PT or are generally more environmentally aware.

Climate concerns are the most important constituent in reducing flights, probably because the connection between flying and climate change is obvious. The second most important factor (shared across the distance ranges) is the number of flights. Older individuals are reluctant to reduce short flights while males are more willing to reduce long-haul flights.

Commenting on gender effects, males are less likely to change dietary preferences, more positively inclined towards CO_2-certificates, and tend to reach the target more frequently.

Installing a heat pump involves a considerable investment. Therefore, it is not surprising that household income has a significant and positive effect. Meanwhile, the household size has a negative coefficient, implying that larger households may simply be capital-constrained and may not regard the investment as feasible.

Commenting on income effects, people living in high-income households tend to be more willing to replace or sell the car, install a heat pump (as just discussed), change dietary preferences, buy certificates, and reach the target more often. If they did not reach the target, they are more willing to accept the proposed offset (explicit nudge). Higher education has very similar effects.

The political latent variable indicates that people further to the right on the political scale tend to reach the carbon target less frequently which seems plausible, as these individuals are generally more critical towards climate change and the need or responsibility to act. However, measures that benefit the housing unit (better insulation of the facade and roof) are more strongly supported. In addition, solar panels are an accepted solution.

Similarly, the income effect suggests, that these measures are also favoured by lower income groups.

From a political perspective and to avoid regressive effects, policy makers could first support improving the quality of the insulation before any subsidies for heat pumps. Similarly, subsidizing new (electric) cars might benefit the affluent population and additionally inhibit behavioral change.

4 Conclusion

This paper looked at preferred pathways to reduce personal carbon emissions by 30%. Individuals were invited to evaluate 16 different reduction strategies and choose the menu that satisfies their preferences. They could choose both the set of strategies (intensive margin) as well as (implicitly) the CO_2-amount they would like to save with the strategy (extensive margin).

For the average respondent, reducing the room temperature is the most acceptable solution while installing controlled ventilation is the least preferred. Installing a heat pump or solar panels is the most prominent housing-related investment. Meanwhile, respondents were reluctant to reduce flying, especially long-haul. Buying CO_2-certificates is a popular choice and an important pathway to reach the reduction target as the amount saved via certificates is usually quite substantial.

Generally, strategies that imply behavioral change only marginally contribute to emission savings. This suggests that the behavioral cost outweighs the technological cost. From this perspective, bold large-scale technological investments to combat climate change (such as solar fields or other renewable energies) will play a pivotal role, as behavioral change is difficult.

Stated climate perceptions and beliefs are important. Individuals with stronger climate concerns are more likely to reach the target and more willing to accept any reduction strategy. In particular, these perceptions and beliefs are the most important constituent in reducing the number of flights.

Owners of electric cars are less willing to reduce annual mileage or switch to public transport. Subsidizing electric vehicles might therefore be accompanied by a second-order effect and the net benefit would need to be reevaluated.

People living in high-income households tend to be more willing to replace or sell the car, install a heat pump, change dietary preferences or buy certificates. It is therefore likely that they simply solve the problem with money or even outsource the emission reduction (with certificates) while lower-income households may have to bear disproportionally more of the behavioral cost. The preferred investment-related strategy for low-income households is insulating the facade.

People further to the right on the political scale tend to reach the carbon target less frequently. Measures that benefit the housing unit (better insulation of the facade and roof), or installing solar panels are accepted solutions. This might be important since right-leaning individuals are generally more critical of climate change and the need to take personal action. Incentivizing these individuals to invest in reduction strategies might therefore be pivotal.

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