”Convincing the clueless? Testing a novel information treatment to increase self-efficacy towards climate action”

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Abstract

Climate change is an urgent problem requiring large scale transformations of societies. An important driver of these changes are individual actions and sufficient support for climate policies. However, so far there is little evidence that commonly advocated methods aimed at triggering behavioral change and policy support such as providing information about the causes and consequences of climate change are effective. I introduce a novel, individualized information treatment, the priority evaluator, to test amongst a nationally representative sample of the Swiss resident population if learning about personal, viable behavioral changes increases self-efficacy - a main determinant for behavioral change and climate action. Contrary to the priority evaluator increases self-efficacy perceptions amongst respondents that are less concerned about climate change and feel less of a personal responsibility to do so, while at the same time reducing self-efficacy perceptions amongst respondents that feel greatly personally responsible. This means that the priority evaluator can update people's perception of their agency to reduce their personal emissions, which in turn is linked to pro-environmental behavior, climate action and particularly more

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policy support for much-needed push measures.

Keywords: Self-efficacy, Pro-environmental behavior, Climate policy support, information treatment, survey experiment

Introduction

Climate change is an urgent problem that requires large scale societal changes to achieve the greenhouse gas emission reduction goals set by the Paris agreement (United Nations Environment Programme, 2022). While a lot of these changes are warranted on a systemic level, there is also a call for individual action. The direct greenhouse gas (GHG) mitigation potential through individual behavioral change is substantive (Andersson and Nässén, 2023; IPCC, 2022; Ivanova, Barrett, Wiedenhofer et al., 2020; Wynes and Nicholas, 2017). Further, individual behavioral changes might help achieve and maintain long-term structural changes by shifting social norms and practices, which in turn again influence people's behaviors (Nielsen, Clayton, Stern et al., 2021; Winkelmann, Donges, Smith et al., 2022). Some scholars argue that focusing on individual GHG contributions distracts from pursuing systemic solutions on a political level (Chater and Loewenstein, 2022; Hagmann, Liao, Chater et al., 2023) and holding powerful actors such as the fossil fuel industry accountable Supran and Oreskes (2021). However, particularly in affluent societies individual behavioral changes and climate actions are inevitable in order to reduce greenhouse gas emissions sufficiently (Wiedmann, Lenzen, Keyßer et al., 2020). Further, individual behavioral change is also not only about what people do as consumers, but also as citizens: Climate actions such as environmental activism as well as supporting climate policies signals demand for climate policies (Stern, 2000) which are likely to translate into policy adaption in democratic political systems (Soroka and Wlezien, 2010; Wlezien, 1995).

The question how to initiate such behavioral change and climate action through different types of interventions has been researched extensively (Nielsen, Clayton, Stern et al., 2021; Steg, 2023). One of the most commonly adopted strategies to induce behavior change is to provide general information on climate change or general advice on how to change behaviors (Abrahamse and Matthies, 2018; Moser and Dilling, 2011). While a lot of these studies increase knowledge and concern about climate change (Abrahamse, Steg, Vlek et al., 2005; Abrahamse and Matthies, 2018), they do not work to change behaviors and climate policy support (Bergquist, Thiel, Goldberg et al., 2023; Owens and Driffill, 2008; Whitmarsh, Poortinga, and Capstick, 2021). Information and knowledge about the negative effects of climate change may be a necessary condition for behavioral change and climate action, but on their own, are insufficient to initiate the desired behavioral changes (Whitmarsh, Poortinga, and Capstick, 2021). Therefore, scholars have been calling for information provisioning that targets specifically additional drivers of pro-environmental behavior and climate actions other than just knowledge about the causes and consequences of climate change (Steg, 2018; van Valkengoed, Abrahamse, and Steg, 2022).

I contribute to this literature by testing a priority evaluation approach (Hoinville, 1971) as an information treatment amongst a representative sample of the Swiss resident population. The research question I address is whether providing people with highly individualized information through a priority evaluator empowers them with the agency required to enact desired changes in environmental behavior

That is, whether highly individualized information can increase their efficacy perceptions by showing them what they can and cannot do on their own. Further, I want to see whether environmental self-efficacy is linked to climate policy support. The priority evaluator is an interactive online tool that assesses preferences for different individual carbon emission reduction scenarios that has been adapted from transport and urban planning (Jäggi, 2015). It provides individualized and therefore realistic information about possible behavioral changes and lifestyle adaptations. It shows the potential impact of changes, both with regards to greenhouse gas emissions as well as financial costs and benefits. This allows individuals to make realistic cost/benefit-analyses of their decisions, emulating real-life decision-making processes.

While the priority evaluator does not affect efficacy perceptions on average, I find clear evidence for heterogeneous treatment effects. The priority evaluator leads, contrary to my expectations, to increased efficacy amongst respondents that are less concerned about climate change, have been less confident about their capacity to reduce their carbon emissions and feel less of a personal responsibility to do so, while at the same time reducing efficacy perceptions amongst respondents that are highly concerned, confident and feel greatly personally responsible. This means that the priority evaluator can realistically update people's perception of their agency to reduce their personal emissions, which in turn is linked to pro-environmental behavior, climate action and particularly more policy support for much needed push measures.

Theory

The role of information treatments in fostering pro-environmental behavior and climate policy support

The most commonly studied approach to initiate pro-environmental behavior and climate action is to provide general information on the causes and consequences of climate change or general advice on how to solve it (Abrahamse and Matthies, 2018; Moser and Dilling, 2011). This approach largely follows an information or knowledge deficit model, which assumes that people fail to behave in an environmentally friendly way because they are unaware of the problem of climate change or do not know what to do about it (Burgess, Harrison, and Filius, 1998; Dietz, 2023*b*; Schultz, 2002). Providing information should overcome such a deficit.

There is a multitude of studies that test this strategy with regards to different behaviors aimed at reducing greenhouse gas emissions such as reducing household energy consumption (e.g. Abrahamse, Steg, Vlek et al., 2005; Delmas, Fischlein, and Asensio, 2013; Iweka, Liu, Shukla et al., 2019; Nemati and Penn, 2020; Nisa, Bélanger, Schumpe et al., 2019), reducing food waste or changing to a more climate friendly diet (e.g. Abrahamse, 2020; Grundy, Slattery, Saeri et al., 2022; Kwasny, Dobernig, and Riefler, 2022) and changing transport behavior (e.g. Doğru, Webb, and Norman, 2021; Semenescu, Gavreliuc, and Sârbescu, 2020). However, these studies provide very little evidence that this kind of information leads to behavioral changes and climate action. While information provisions can lead to more knowledge about causes and consequences of climate change and increase concern about it, behavioral changes are usually not observed (Bergquist, Thiel, Goldberg et al., 2023; Staats, Wit, and Midden, 1996).

The reason for this lack of empirical support for the effect of information treatments on behavioral change and climate action is multifold. First, meta-analyses and reviews seem to group different types of information treatments together despite their differentiated impact on behaviors (e.g. information on the causes of climate change and provision of feedback on the environmental impact of one's behavior), making it difficult to determine which intervention works and why (van Valkengoed, Abrahamse, and Steg, 2022). Second, information treatments have been predominantly focusing on increasing knowledge. This neglects important behavioral insights into pro-environmental behavior and climate action. Knowledge about the reality of (anthropogenic) climate change does not automatically translate into climate actions but is rather a necessary condition for people to engage in pro-environmental behavior (Hornsey, Harris, Bain et al., 2016; Steg, Perlaviciute, and van der Werff, 2015). The discrepancy between pro-environmental attitudes and climate action is commonly referred to as the attitude-behavior gap (Kollmuss and Agyeman, 2002).

Given these problems, recent research has been trying to make a case for a more careful theorization about how different interventions work - namely, that interventions need to target specific determinants of behavioral change and climate action in order to be potentially successful (Michie, Carey, Johnston et al., 2018; van Valkengoed, Abrahamse, and Steg, 2022). A promising theory to identify effective intervention points is a widely applied and integrative theoretical model of behavior - the theory of planned behavior (Ajzen, 1985, 1991). The theory of planned behavior (TPB) is a general theoretical framework aimed at understanding how people make decisions and take actions. It is not specific to pro-environmental behavior and climate action and has been applied to a wide variety of different behaviors in areas such as transport or health (Dietz, 2023*a*). In its basic formulation, one of the main determinants of behavioral intentions and subsequently behaviors is a feeling of efficacy or perception of behavioral control (Bandura, 1978). People that have an intention to engage in certain behaviors additionally need to feel that they are capable to do so. The theory, therefore, provides a plausible explanation for the often-observed attitude-behavior gap and the lack of evidence for information-based interventions' effects on initiating pro-environmental behavior and climate action (Kollmuss and Agyeman, 2002). People's intentions to reduce their greenhouse gas emissions based on knowledge about climate risks as well as their pro-environmental values often do not translate in climate action because people lack the perception of agency as they are uncertain about what to do and how effective it would be.

There are numerous studies documenting that perceived behavioral control is strongly correlated with whether a person behaves environmentally friendly or supports environmental policies (van Valkengoed and Steg, 2019): Examples include the use of public transportation (Heath and Gifford, 2002; Kaiser and Gutscher, 2003; Javaid, Creutzig, and Bamberg, 2020) or the purchase of fuel hybrid or electric cars (Peters, de Haan, and Scholz, 2015; Wang, Fan, Zhao et al., 2016), the installation of renewable energy systems (Whitmarsh and O'Neill, 2010; Wolske, Stern, and Dietz, 2017) and buying organic products (Scalco, Noventa, Sartori et al., 2017). There is less empirical work on the lack of self-efficacy, but Mayer and Smith (2019) demonstrate that fatalistic beliefs about the possibility to slow down or prevent further climate change' reduce behavioral and policy response to climate change. Additionally, while recent research provides mixed evidence that efficacy perceptions can be manipulated experimentally (Geiger, Swim, and Fraser 2017; Hornsey, Chapman, and Oelrichs 2021, 2022), there is evidence that more interactive information treatments such as games or simulations were successful in doing so (Fox, McKnight, Sun et al., 2020; Peng, 2008).

On the other hand, there is very little research that looks into how efficacy beliefs are related to climate policy support. Most of the research looking into the link between efficacy perceptions and political pro-environmental behavior has looked into activism and protest participation as a form of public sphere pro-environmental behaviour (Stern, 2000; Hamann and Reese, 2020; Jugert, Greenaway, Barth et al., 2016; Lee, Kim, Kim et al., 2014; Wallis and Loy, 2021). However, the measures used for efficacy are more generally regarding political efficacy (Anderson, 2010). To the best of my knowledge, there is only one study that has looked into how the perceived capacity of changing one's own behavior in order to reduce carbon dioxide emissions is related to climate policy support (Kukowski, Hofmann, Roozenbeek et al., 2023). The theoretical assumption linking efficacy perceptions and policy support hereby is not directly derived from TPB. Rather, the theoretical assumption relates to policy proximity, or the extent to which a policy will affect individuals (Huber and Wicki, 2021; Pleger, 2017; Soss and Schram, 2007). It is reasonable to assume that self-efficacy perceptions are directly linked to cost perceptions of policies. How costly (both financially and behaviorally) a policy is for an individual has been shown to be a strong predictor of climate policy support (Drews and van den Bergh, 2016). Presumably, people who think they're capable of behavioral change will be less affected by a policy targeting that behavior and may therefore perceive it as less personally costly.

The priority evaluation approach

Recently, more interactive tools have been developed as information treatments. For example carbon calculators have been assessed regarding their role in promoting pro-environmental behavior (Büchs, Bahaj, Blunden et al., 2018; Kok and Barendregt, 2021; Salo, Mattinen-Yuryev, and Nissinen, 2019). However, while they provide personalized information about environmental consequences of behaviors, many of them do not target self-efficacy perceptions as they do not provide personalized information about what behavioral adaptations are available and what costs and benefits of them are. Other more interactive treatments are serious games or simulations (i.e., games not primarily targeted to entertain but to educate), however most of the studies assessing them did not include an experimental setting that would make it possible to estimate the effects of these games on efficacy perceptions, behavioral intentions or even real-world behaviors (Fernández Galeote, Rajanen, Rajanen et al., 2021; Hallinger, Wang, Chatpinyakoop et al., 2020). Recent studies that assessed the effect of serious games or simulations scientifically provide some evidence that next to increasing knowledge about negative consequences of climate change (Hüttel, Heitzig, Smith et al., 2022; Nussbaum, Owens, Sinatra et al., 2015), they also were able to increase efficacy perceptions (Fox, McKnight, Sun et al., 2020) or behavioral intentions (Cerf, Matz, and MacIver, 2023). The priority evaluator presented as an extended information treatment here is an interactive online tool to assess preferences for different carbon emission reduction scenarios (Jäggi, 2015), that has its origins in urban and transport planning (De Gruyter, Currie, Truong et al., 2019; Hoinville, 1971; Permain, 1989). The priority evaluator allows respondents to interactively reduce their CO2-emissions to a predefined target through different, individualized behavioral adaptations, while at the same time transparently showing the respective (financial) costs and benefits. This makes the priority evaluator particularly well suited to affect efficacy and behavioral control beliefs. More concretely, the priority evaluator allows individuals to evaluate the personal financial costs and benefits of certain behavioral changes and lifestyle adaptations (as well as indirectly their behavioral costs and benefits such as effort, time, inconvenience by thinking about these options), and trade them off against the respective environmental benefits of these adaptations. The strength of the priority evaluator hereby lies in providing individualized information about the financial costs and benefits of behaviors, as the literature finds that people are notoriously bad in estimating true costs of their behaviors, such as the total costs of car ownership (Andor, Gerster, Gillingham et al., 2020), or household energy costs (Blasch, Boogen, Daminato et al., 2021). Further, the priority evaluator provides dynamic feedback about the changes in greenhouse gas emissions of specific behavioral adaptations, as people usually lack information on the effectiveness of their GHG emission related behaviors (Attari, DeKay, Davidson et al., 2010; Camilleri, Larrick, Hossain et al., 2019; Cologna, Berthold, and Siegrist, 2022; Wynes, Zhao, and Donner, 2020). Thus, the priority evaluator can be expected to affect efficacy and control beliefs regarding the reduction of carbon emissions. It enables people to assemble personalized set of behavioral changes that ideally can effectively lower their greenhouse gas emissions to meet a predefined target. The priority evaluator provides heavily personalized, realistic information on how one can do something, and is therefore directly targeting self-efficacy perceptions and perceived behavioral control. Depending on whether these adaptations seem feasible or not to the user, efficacy perceptions can be expected to be affected differently.

The priority evaluator is likely to influence individuals' beliefs in their efficacy and control over reducing carbon emissions. It enables people to tailor a personalized set of behavioral changes that ideally can effectively lower their greenhouse gas emissions to meet a predefined target.

Empirical expectations

Overall, the priority evaluator serves as an interactive, experiential information treatment that allows to try out different ways of reducing personal carbon emissions. While some strategies might be more behaviorally costly, others allow to maintain current behaviours but are more expensive. In any case, the priority evaluator allows to optimize personal carbon emission reduction in a way that most people would not have had a chance to before, and should thus lead to a higher level of perceived self-efficacy. I therefore expect:

H1: Using the priority evaluator increases self-efficacy perceptions on average.

The reason why previous research did not identify average effects of information treatments is likely due to the fact that treatments produce heterogeneous effects based on individual characteristics, such as environmental concern and climate change related risk perceptions (Kok and Barendregt, 2021). In our case, only people that want to act (they have an intention based on pro-environmental attitudes as well as pro-environmental norms (Ajzen, 1985)) and think climate change is a serious problem but lack self-efficacy might experience a raise in self- efficacy because the priority evaluator can demonstrate that certain mitigation measures have quite a big relative impact on individuals carbon budgets (e.g. making trips by train instead of flying, see above). In contrast, certain people might find it hard to reduce their emissions (e.g., due to their comparatively low emission level and/or financial constraints) when using the priority evaluator due to their comparatively low emission levels and/or financial constraints. I therefore expect the following additional pattern:

H2a: Using the PE increases self-efficacy among individuals with higher levels of risk perception.

H2b: Using the PE increases self-efficacy among individuals with higher levels of pro-environmental norms.

H3a: Using the PE decreases self-efficacy among individuals with low emission levels.

H3b: Using the PE decreases self-efficacy among individuals with low levels of household income.

As previously mentioned, providing general information on environmental problems or general advice does usually not affect environmentally relevant behaviors (Owens and Driffill, 2008) and policy preferences. However, changes in self-efficacy might lead to changes in policy support (i.e., self-efficacy is a mediator, similar to other types of pro-environmental behavior). Based on the assumption that the priority evaluator has heterogeneous effects on self-efficacy beliefs, I would also expect that climate policy support is particularly increased amongst those respondents for which the priority evaluator increases self-efficacy-perceptions in the first place. I therefore further expect:

H4: Using the priority evaluator increases climate policy particularly amongst individuals that increase their self-efficacy perceptions.

Data and methods

Survey instrument and data collection

The empirical analysis relies on original data from Wave 3 (Spring 2022) of the Swiss Mobility Panel (Lichtin, Smith, Wehrli et al., 2023). The SMP is a longitudinal panel drawn from a nationally representative sample of adult (18 - 80 years) residents of Switzerland. Surveys of the SMP are implemented semi-annually. The first initial baseline recruitment wave took place in autumn 2020. Respondents (panel members) were recruited from a random sample drawn from household registry data provided by the Swiss Federal Statistical Office, stratified by statistical region (NUTS-2). Respondents were invited to participate in the online panel survey via postal letter. The response rate for Wave 1 (panel recruitment and baseline survey) was 32.89%. The sample was checked against population demographic characteristics and was found to be representative. Wave 3 of the SMP has a total of n=5'941 completed responses. The analytical sample consists of n=3779 responses (see Table A1 in the appendix). The project study design, instruments and data collection methodology was approved by the ETH-Zurich Ethics Board (EK-2021-N-94). Respondents were first provided with an informed consent form upon entering the survey. Only respondents that consented to their participation were directed to the survey instrument. The survey was available in English, French, German and Italian. The full survey instrument is available online (ISTP, 2023).

Research design

This study applies two research designs. First, it follows a population-based survey experimental design that allows drawing causal inferences about the Swiss resident population (Mutz, 2011). The experimental design follows a post-only design to test H1, H2a/H2b and H3a/H3b, which means the outcome variable is measured post-treatment only (Clifford, Sheagley, and Piston, 2021). Respondents get assigned randomly to two groups. While the control group (Split A, Full sample N=2051) only gets questions about their carbon budget, their perception of climate change risks and efficacy, the treatment group (Split B, Full sample N=1942) additionally fills out the Priority Evaluator as well as subsequent questions assessing their self-efficacy post-treatment. Both groups get asked policy questions towards the end of the survey. Figure 1 shows an illustration of the survey flow. More detailed illustrations of the survey flow and the experimental design can be found in the appendix (Figure A1). For some respondents, the Priority Evaluator did not work in the online survey. These respondents have been excluded from the analysis. This is why the analytic sample for Split B is somewhat smaller (n = 1'729). However, a balance check demonstrates that there is no systematic reason for the Priority Evaluator to fail, leaving Split B unbiased (see Appendix Figure A2).

The priority evaluator as treatment

Figure 2 presents a screenshot of the priority evaluator used for this study. Based on a survey-embedded carbon calculator, an individual's annual CO2-emission level is calculated, covering three sources of individual emissions: transport, food and housing. The emissions are visually displayed as a stacked bar ("Current Emissions") consisting of the emissions for transport (blue), food (purple) and housing (orange). A second bar (green) displays an emission reduction target ("Emissions Target"), which is in this study a relative reduction target of 30 percent (i.e., 70 percent of respondents initially calculated emissions). These bars are static, while a third bar in the middle dynamically visualizes how one's emissions are affected when changing certain behaviors or making changes to one's mobility tools or home ("Emissions after changes"). This can be done by indicating the type of adaptation in the table to the right. The availability of these adaptation measures is dependent on the respondents

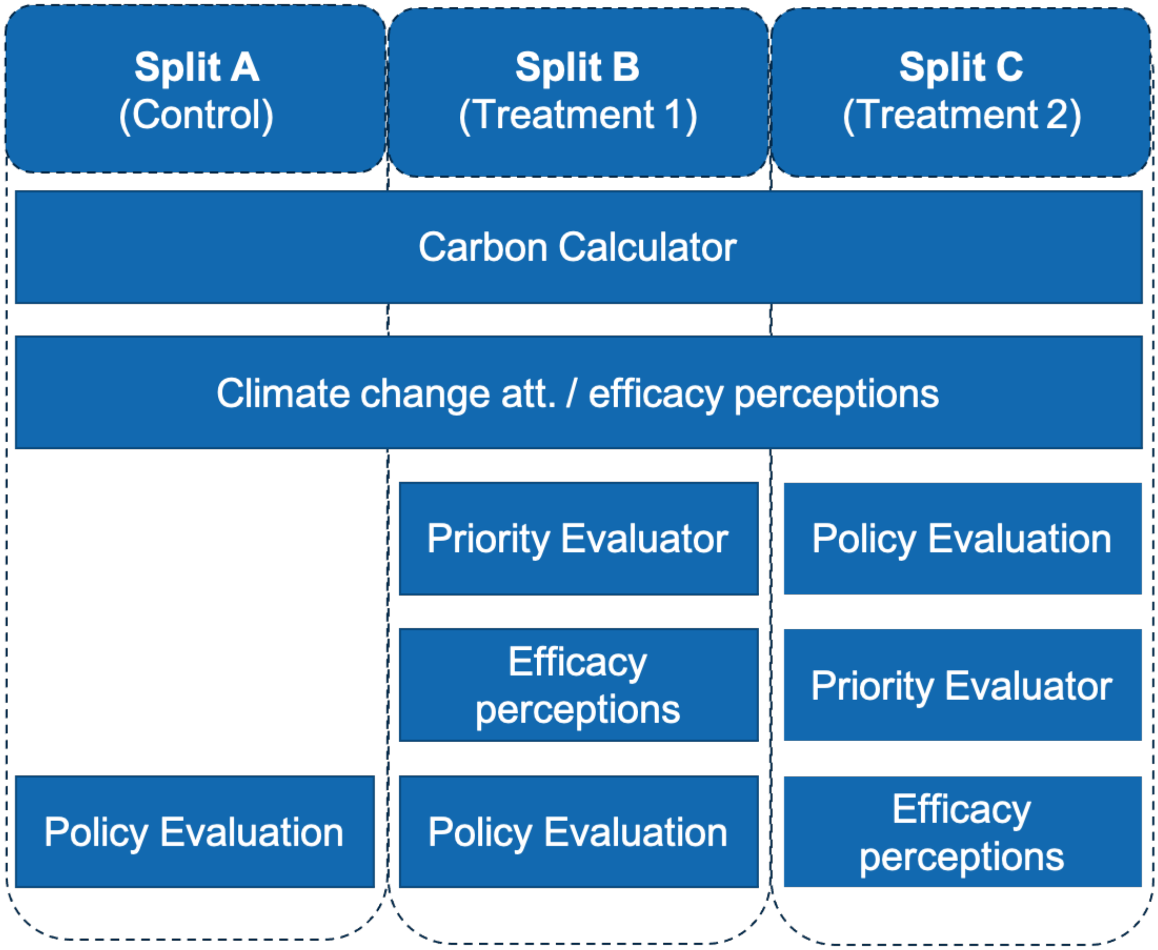

Figure 1: **Illustration of survey flow.**

previously stated living conditions and behaviors (e.g., car/home ownership, number of annual flights taken, annual km driven, etc.). While the chosen adaptions have an influence on the CO2-emission level ("Emissions after changes"), the priority evaluator also indicates the one-time and annual costs or savings for each adaptation as well as the sum of it. In Figure 2, the option to insulate the roof has been chosen, which results in one-time costs of 20'535 CHF, and annual savings of 56 CHF, while also lowering the annual CO2-emissions by approx. 2.5 tons. This option is only available to respondents that indicated in the survey that they own and live in a detached or semi-detached house, as for renters or people living in a flat this is usually not something they can decide over themselves. Eventually, the horizontal bar on the bottom will turn green once the emission target has been reached.

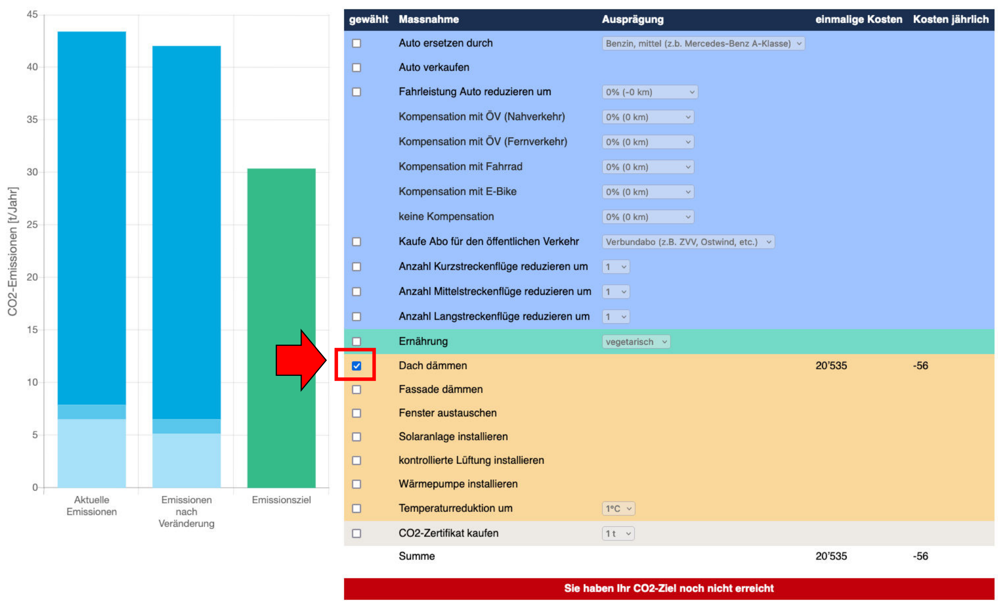

Figure 2: **Screenshot of the priority evaluator.**

Operationalization

Self-efficacy perception The main concept of interest is perceived self-efficacy regarding carbon emission reductions. The item adopted is based on an item from the European Social Survey, Wave 8 (European Social Survey, 2016) special module on 'public attitudes to climate change', measuring the extent of how confident or not somebody feels being able to reduce one's own carbon dioxide emissions. The outcome ranges on a scale from 0 'Not at all confident' to 10 'Completely confident'.

Climate policy support The second outcome is climate policy support. Analogous to the adaptation measures in the priority evaluator, the survey items cover the three sectors mobility, food, and housing. The items are also covering a range of policy designs (push vs. pull, market-based vs. non-market based, see (Wicki, Fesenfeld, and Bernauer, 2019) for a discussion). The items used measure the extent of how much somebody is in favour or against a specific climate policy on a 5-point Likert scale ranging from 1 'Very much against' to 5 'Very much in favour'.

Subgroup characteristics Finally, subgroups are operationalized as followed: First, climate change concern is measured using an item from the European Social Survey, Wave 8 (European Social Survey, 2016) special module on 'public attitudes to climate change', measuring the extent to how much somebody is worried about climate change. The outcome ranges on a scale from 1 'Not at all worried' to 5 'Extremely worried'. To measure pro-environmental personal norms, also an item from the European Social Survey, Wave 8 (European Social Survey, 2016) special module on 'public attitudes to climate change' is used, measuring to what extent somebody feel you has a personal responsibility to try to reduce carbon dioxide (CO2) emissions. The outcome ranges on a scale from 1 'Not at all' to 10 'A great deal'. Unfortunately, due to a coding error, the values '7' and '8' have been collapsed to '7'. To explore income groups an item asking about respondents' net household income, ranging from 1 'below 2'000 CHF per month' to 11 'over 18'000 CHF per month' has been used to create four different groups. They are defined as followed: 1 ('below 2'000 CHF per month' to '4'001 - 6'000 CHF per month'), 2 ('6'001-8'0000 CHF per month' to '10'001 - 12'000 CHF per month'), 3 (12'001 - 14'000 to '16'001 - 18'000 CHF per month') and 4 ('above 18'000 CHF per month'). Last, respondents were categorized based on their estimated carbon emissions from the carbon calculator that was implemented in the survey. Here, respondents were grouped into four equally sized groups to differentiate between emission levels. Values range from 1 (1.45 t CO2 to 9.69 t CO2), 2 (9.69 t CO2 to 20.7 t CO2), 3 (20.7 t CO2 to 34.0 t CO2) and 4 (34.1 t CO2 to 972 t CO2).

Analytic Strategy

In order to test H1, I estimate an average treatment effect (ATE) which demonstrates whether self-efficacy on average is different for the treatment group (Split B) compared to the control group (Split A) measured after the treatment. The average treatment effect is calculated by estimating the difference in means for self-efficacy of the treatment (Split B) and control group (Split A) using a simple OLS regression model that regresses self-efficacy on a binary treatment variable. I show predicted values for ease of interpretation.

In order to test H2a and H2b as well as H3a and H3b, i.e., to assess whether the effect of the priority evaluator on self-efficacy perceptions differs depending on respondents' characteristics, conditional treatment effects (CTE) are estimated. It is important to note that this effect only describes whether the effect of the treatment is descriptively different across levels of the moderating variable (Kam and Trussler, 2017). This is most commonly done by testing for interactions, and more specifically by incorporating an interaction term between the treatment variable and the observed variable that defines the subgroup of interest in the regression model of the outcome. In this way, it can be determined if the treatment has a substantive and significant difference in effect for the population subgroup of interest (in contrast to analyzing subgroups separately (Cintron, Adler, Gottlieb et al., 2022)). I follow (Hainmueller, Mummolo, and Xu, 2019) and estimate interaction effects for the dichotomous treatment and the continuous moderator as well as the dichotomous treatment and the continuous moderator breaked into several bins in order to allow for nonlinear interaction effects and safeguard against excessive extrapolation.

I follow the same procedure to test H4, but using climate policy support as the dependent variable.

All analyses were performed using the statistical software R version 4.1.0 (R Core Team, 2023).

Results

Engagement with priority evaluator

First, it is important to assess whether respondents actually engaged with the priority evaluator in a meaningful way. Table 1 shows thus summary statistics for respondents in the treatment groups regarding their interaction with the priority evaluator (Split B, n = 1'728). Respondents spent on average 2 minutes on the exercise, and made 25 adjustments (measured in clicks, see Figure A7 for distributions). Both cost and difficulty perceptions have a mean value of 5.4 which is close to the middle category of the respective measurement instruments (i.e., between 'not at all difficult/expensive' and 'extremely difficult/expensive').

Table 1: **Summary Statistics**

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
PE timer (min)	1728	2.2	6	0.053	0.86	2.7	223
PE click count	1728	24	26	1	7	33	223
PE cost perception	1551	5.4	2.6	0	4	7	10
PE difficulty perception	1573	5.4	2.5	0	4	7	10

Figure 3 provides further information about how respondents interacted with the priority evaluator (Split B, n = 1'728). Panel A shows that, unsurprisingly, measures that are behaviorally and financially less costly are mostly chosen (i.e., reduce car mileage, change diet, reduce room temperature) - both amongst respondents that reached the target and those that did not. In contrast, those measures that are behaviorally or financially costly and are only available to a smaller share of respondents are less often chosen (e.g., respondents giving up their car or refurbish their house).

Panel B shows that, of all respondents in the treatment arm, approximately 50% of respondents reached their emission reduction target. Panel C provides a closer look on the distribution of how much of the reduction target was met shows - and here there are some noteworthy points: First, there are approximately 1/4 of respondents that seemingly did not engage at all with the tool or chose not to reduce their emissions at all or only very little. However, approx. 1/4 of respondents seemingly tried to reduce their emissions but did not reach the target. Another 1/4 either reached the target or overshot the target by a bit. The last 1/4 of respondents reduced their emissions much more than required (up to two or three times what was required).

In sum, this provides first evidence that respondents to a large degree engaged meaningfully with the priority evaluator. However, a non-negligible share of respondents did not engage with the priority evaluator or refused to reduce their emissions. Subsequent analyses need to take this into account.

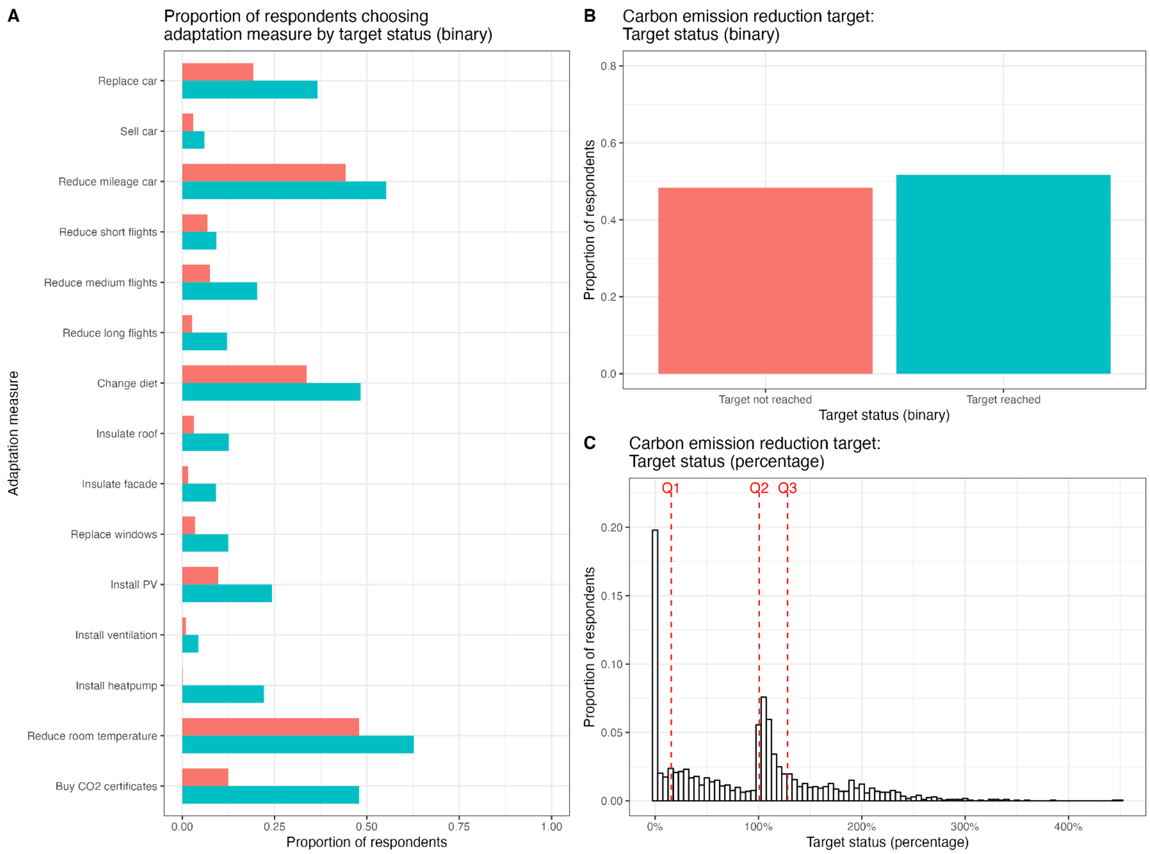

Figure 3: **Engagement with priority evaluator.** Figure 3A indicates for each adaptation measure what proportion of respondents that reached the target (blue bars) or not (red bars) choose the respective adaptation measure (Split B, $n = 1'728$). Figure 3B shows the proportion of respondents that reached the target (blue bar) or not (red bar) (Split B, $n = 1'728$). Figure 3C shows the distribution of how much of the emission reduction target was reached. 100% means the reduction target was met exactly. Quartiles of the distribution are indicated by red dashed lines (Split B, $n = 1'728$).

Treatment effect of the priority evaluator on self-efficacy perceptions and within-subject changes in self-efficacy perceptions

Figure 4a shows the predicted value of perceived self-efficacy for both the control and treatment group on a scale from 1 to 10. As can be seen by the overlapping confidence interval and the regression results (Table A5), there is no statistically significant difference between those two values, and therefore no direct effect of the treatment on self-efficacy perception. In order to see however whether there might be effect heterogeneity, Figure 4b displays the distribution of within-person changes of self-efficacy perception. Indeed, while on average there is no change, this might be also due to the fact that people gained approximately as much self-efficacy through the experiment as they lost.

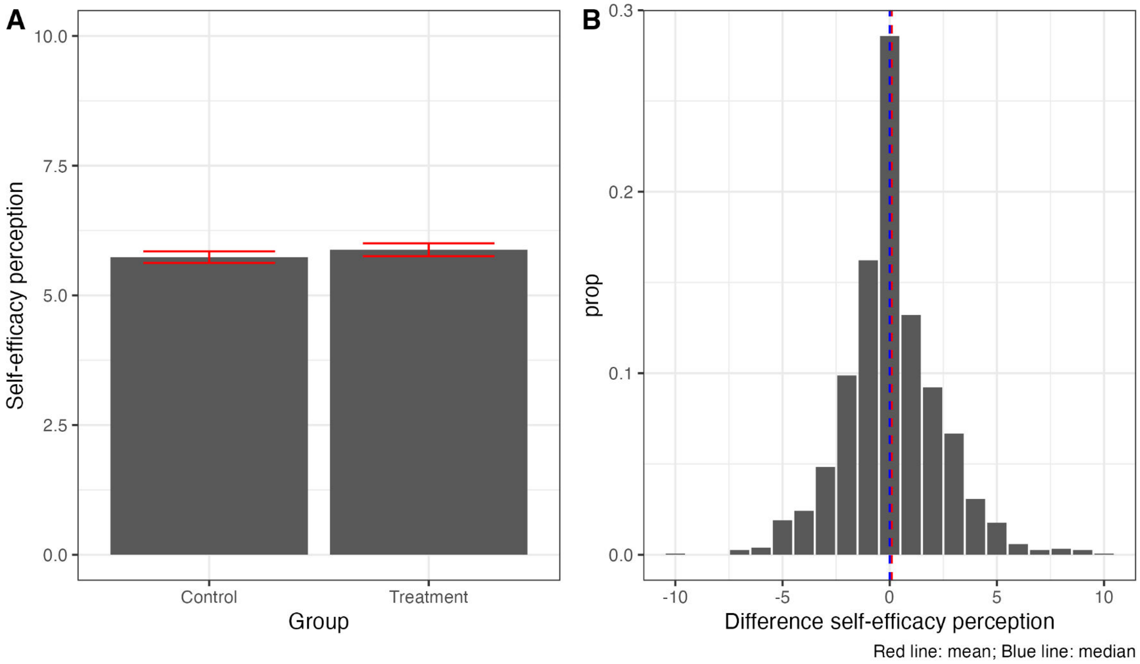

Figure 4: **Predicted value of self-efficacy perception by treatment/control group and distribution of within-person changes of self-efficacy perceptions for the treatment group.** Bars in Figure 4A (+/- 95% confidence interval) indicate the average predictions of self-efficacy perception by control and treatment group. Predictions are based on OLS linear regression estimates (Split A and Split B, n = 3'779). The underlying regression results for Figure 4A can be found in the appendix (Table A5). Bars in Figure 4B indicate the absolute number of respondents by changes in self-efficacy perception (difference between pre- and post-treatment-measurement in Split B, n = 1'728).

Heterogeneous treatment effects of the priority evaluator on self-efficacy perception

Figure A8 shows differences in predicted values of self-efficacy perceptions by different individual characteristics and control/treatment group. Figure A8a shows that self-efficacy perceptions are highly associated with different levels of climate change concern pre-treatment. While an individual who states to be not at all worried about climate change can be expected to have on average a self-efficacy score of 2, somebody who states to be extremely worried can be expected to have on average a self-efficacy score of 7 pre-treatment. Figure A8b shows that there is also a positive association between pro-environmental personal norms and self-efficacy perceptions pre-treatment. When comparing pre- and post-treatment values of perceived self-efficacy, there are some noteworthy differences observable. Among respondents with lower levels of climate change concern, the treatment seems to increase self-efficacy perceptions, while the opposite is the case for respondents with high levels of concern, although there the difference is below the level of significance as indicated by overlapping confidence intervals. When looking at differences in self-efficacy perception by pro-environmental personal norms, for people with very low levels of pro-environmental personal norms the treatment also seems to increase self-efficacy perceptions, while the opposite is true for people that indicate that they feel a great deal personally responsible to reduce their emissions.

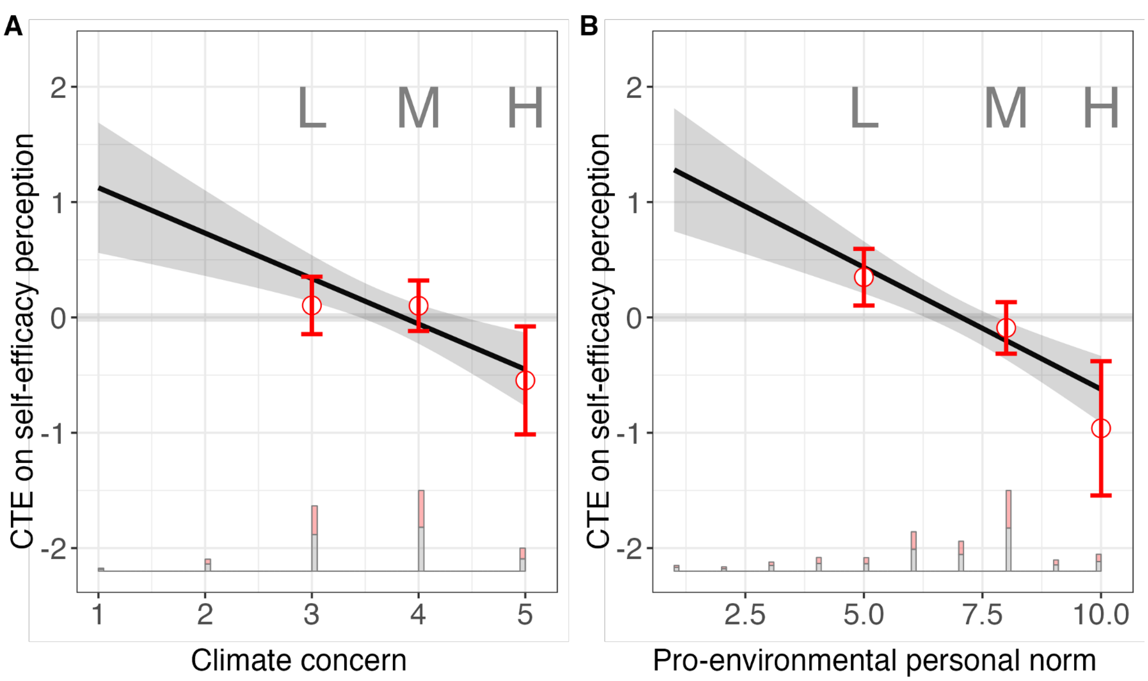

Figure 5: **Marginal effects of treatment on self-efficacy perception by climate change concern/pro-environmental personal norm.** Red dots with vertical lines and black line with grey errorband indicate marginal effects (+/- 95% confidence interval) of self-efficacy perception across different levels of climate concern/pro-environmental personal norms. Marginal effects are calculated from both OLS linear regression estimates and binning estimator estimates as described in (Hainmueller, Mummolo, and Xu, 2019). Split A and Split B, $n = 3'779$.

Figure A9 shows predicted values for self-efficacy perceptions by different individual characteristics and by treatment/control group. Self-efficacy perceptions seem to be only weakly associated with different levels of an individuals' carbon emission level pre-treatment. However, there are differences in levels of self-efficacy perceptions amongst respondents' levels of household income pre-treatment. Respondents with a net household income between 12'001 and 18'000 CHF per month have on average a higher perception of self-efficacy of 1.5 compared to respondents with a household income between 0 and 6'000 CHF per month on a 11-point scale. The relationship seems to be u-shaped, as the income group with the highest net household income (above 18'000 CHF per month) has again a lower level of perceived self-efficacy pre-treatment than the income group below. When comparing pre- and post-treatment values of perceived self-efficacy, there are no significant differences between self-efficacy perceptions amongst different emission levels or different levels of household income between the treatment and control group.

An alternative estimation approach that treats the conditioning individual characteristics as continuous variables and corrects for extrapolation (Hainmueller, Mummolo, and Xu, 2019) corroborates these results (see Figure 5 and Figure 6 in the appendix).

How changes in self-efficacy affect climate policy support

Last, I expected the priority evaluator to increase climate policy support amongst those individuals for which the priority evaluator increased self-efficacy perceptions. Similar to the effect of the priority evaluator on self-efficacy perceptions, it is thus not surprising that there are no average effects on climate policy support (see Figure A10 in the appendix). I thus only show results for conditional treatment effects for those groups where I found that the priority evaluator positively influenced self-efficacy perceptions. Results for other groups can be found in the appendx (see Figure A11, Figure A12 and Figure A13).

Figure 7 shows marginal effects of the treatment on climate policy support by different levels of pro-environmental personal norm. In contrast to what was expected, there is no increase in climate policy support amongst those respondents for which the priority evaluator increased self-efficacy perceptions (i.e., those with lower levels of pro-environmental personal norms). changes in climate policy support, there is no effect

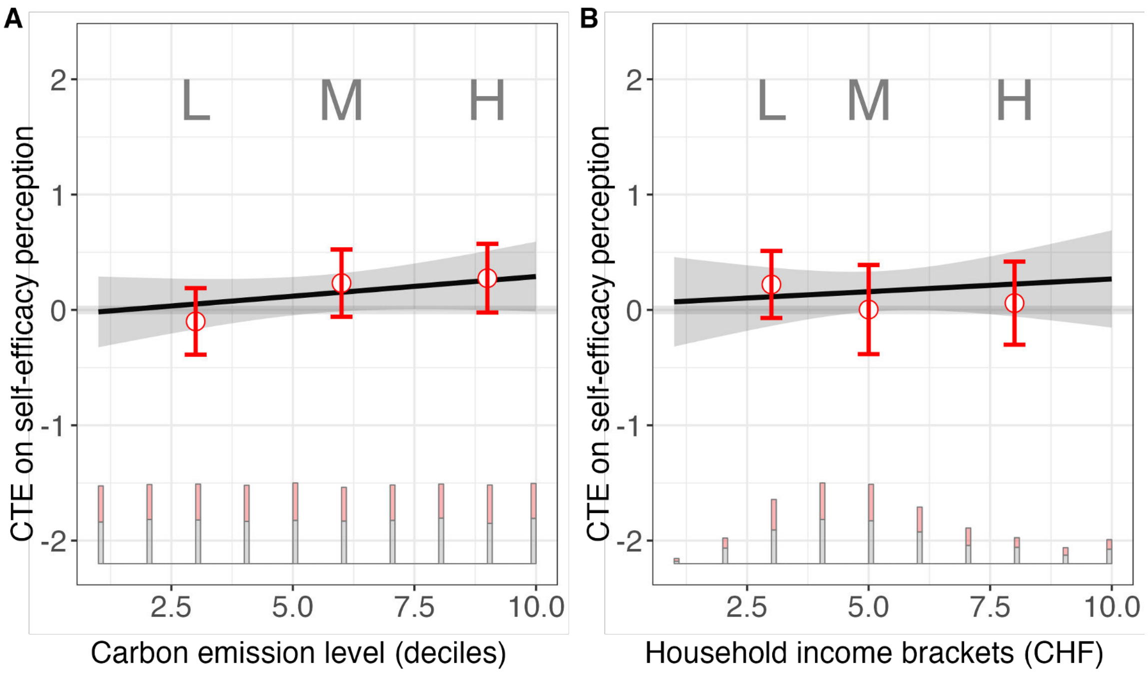

Figure 6: **Marginal effects of treatment on self-efficacy perception by personal carbon emissions/household income.** Red dots with vertical lines and black line with grey errorband indicate marginal effects (+/- 95% confidence interval) of self-efficacy perception across different levels of personal carbon emissions/household income. Marginal effects are calculated from both OLS linear regression estimates and binning estimator estimates as described in (Hainmueller, Mummolo, and Xu, 2019). Split A and Split B, n = 3'779.

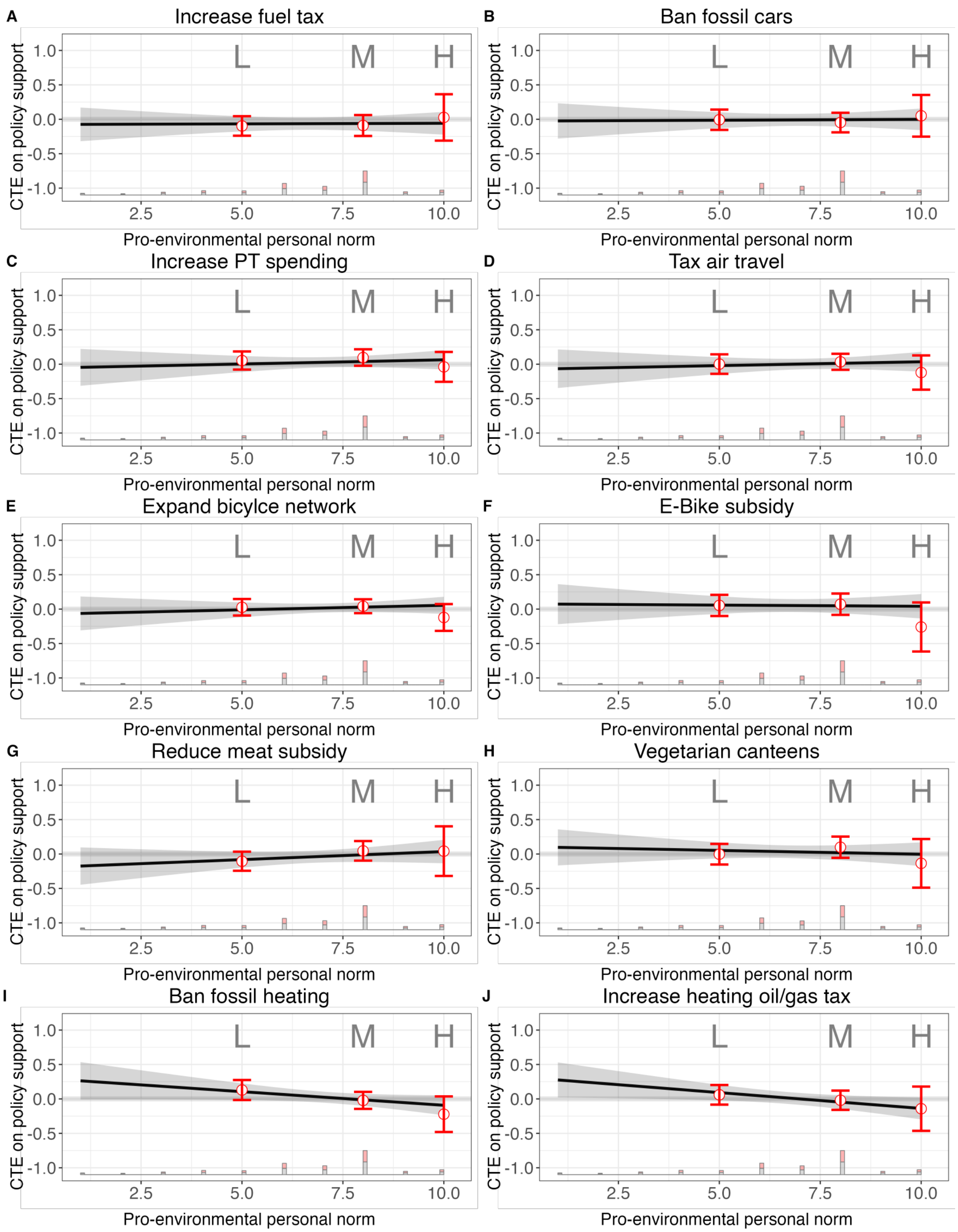

Figure 7: **Marginal effects of treatment on climate policy support by pro-environmental personal norm.** Red dots with vertical lines and black line with grey errorband indicate marginal effects (+/- 95% confidence interval) of self-efficacy perception across different levels of pro-environmental personal norm. Marginal effects are calculated from both OLS linear regression estimates and binning estimator estimates as described in (Hainmueller, Mummolo, and Xu, 2019) Split A and Split B, n = 3'779).

Discussion

To be written...

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Disclosure Statement

The author reports that there are no competing interests to declare.