Public support for different CO2 pricing policies: A factorial survey experiment in the German Longitudinal Environmental Study (GLEN)

2026

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GLEN Technical Report No. 3

Cite as: Wolter, F., Auspurg, K. & Diekmann, A. (2026). Public support for different CO_2 pricing policies: A factorial survey experiment in the German Longitudinal Environmental Study (GLEN). GLEN Technical Report No. 3. https://doi.org/10.31235/osf.io/utyzj_v1

1 Overview

This technical report presents the design and technical setup of a (multi-)factorial survey experiment (FSE) on support for CO_2 pricing policies, which was implemented in an online Inter-wave survey of the German Longitudinal Environmental Study (GLEN) in 2025. GLEN is a nationwide panel survey on environmental and related topics among the German-speaking adult resident population in Germany, funded by the German Research Foundation (DFG; Auspurg, Best, Bozoyan, Diekmann, & Schmiedeberg, 2024).[1] The data of the FSE are published as part of the regular GLEN data releases and are freely available for interested researchers. The purpose of this report is to document the design and technical features of the module, to provide guidelines for data analysis, and to serve as a citable reference for data users, who are asked to cite this technical report as well as the Release-DOI of the GLEN dataset when publishing with these data.

The topic addressed by the FSE pertains to public attitudes and beliefs regarding CO_2 pricing policies, also known as carbon pricing. CO_2 pricing is widely considered a key policy instrument to mitigate climate change (e.g., Boyce, 2018; Carrattini, Carvalho, & Fankhauser, 2018; Döbbeling-Hildebrandt et al., 2024; Sen, Sadikoglu, Ji, & van der Werf, 2024). It works by charging CO_2 emitters a fee based on the amount of CO_2 they release, effectively increasing the price consumers pay for each unit of fossil fuel they purchase. This creates a financial incentive to reduce emissions. However, even though the public is largely concerned about climate change and generally in favor of pollution-reducing measures, pricing mechanisms such as carbon taxes often encounter considerable public opposition (Dechezleprêtre et al., 2025; Douenne & Fabre, 2022; Fairbrother, 2022; Sommer, Mattauch, & Pahle, 2022). The FSE addresses the question why this might be the case. The issue dealt with is hence situated within environmental social sciences and concerns several scientific domains, namely environmental sociology, economics, psychology, and political science, as well as other related fields.

[1] Further and continuously updated information on GLEN can be retrieved online at www.glen-studie.de.

Multifactorial survey experiments are by now established standard tools to study causal mechanisms by experimentally varying several treatments simultaneously and assessing their effects on one or more outcome questions. This ensures high internal validity. Implementing them in high-quality population surveys, such as GLEN, aims to combine this feature with a high external validity and generalizability (Auspurg & Hinz, 2015; Treischl & Wolbring, 2022). The core of the FSE on CO_2 pricing consists of descriptions of different CO_2 pricing policies (price level and use of the public revenues raised by CO_2 pricing) and their application to different example households (with varying income and varying behavioral opportunities to adapt to the costs induced by CO_2 pricing). Additional information treatments experimentally present or withhold information on some of these and further aspects of CO_2 pricing. Three outcome questions are asked: the perceived fairness of the prices to be paid; the perceived effectiveness of the policy, i.e., the perceived likelihood of it inducing behavioral change in the form of reduced carbon emissions; and overall support for it.

Section 2 of this technical report describes the FSE content (experimental treatments and their verbal implementation, outcome questions) and its technical setup. Section 3 depicts the GLEN survey implementation and the ensuing respondent sample. Section 4 provides a description of the resulting dataset and advice for data use.

2 Description of the Factorial Survey Experiment: Treatments, Outcomes, and Technical Setup

2.1 FSE Content: Experimental Treatments and Outcomes

The FSE was developed for being implemented in the online self-administered part of GLEN, ensuring multi-device compatibility (e.g., desktop, smartphone). The module, after an introduction screen containing content-related and technical information, presents to each survey respondent one short scenario-based description (*'vignette'*) of a fictitious example individual with certain characteristics, to whom a specific CO_2 policy scheme is applied. The design incorporates five substantive experimental treatments (referred to interchangeably as *'attributes'*) related to CO_2 pricing schemes and the

example individual, as well as three information treatments. Table 1 gives an overview of these treatments and their levels.

Table 1: Attributes and Levels Used in the Multifactorial Survey Experiment

Nr.	Attribute (Number of Levels)	Levels
Substantive attributes		
1	Monthly costs due to CO_2 pricing (6)[a]	5 €; 10 €; 20 €; 40 €; 60 €; 100 €
2	Revenue use (6)	100 percent payoff per-capita 50 percent payoff per-capita Payoff to low-income households Lower electricity prices for all citizens and companies Lower electricity prices for all companies Financing of climate-protection projects
3	Monthly net income of example individual (4)	1,500 € 2,500 € 4,200 € 7,000 €
4	CO_2 reduction measure (4)[b]	Use public transport (time costs) Lower room temperature (comfort costs) Switch from high-powered petrol to smaller e-car (monetary costs) Install new heating at home (monetary costs)
5	CO_2 reduction costs (2)[b]	Low High
Information treatments		
A	Aim of CO_2 pricing (2)	Empty (i.e., no information provided) Information provided
B	Anchor CO_2 price (3)	Empty (i.e., no information provided) Information provided: monthly costs 10 € in 2025 for average citizen Information provided: monthly costs from few € up to >100 € for average citizen
C	Behavioral opportunities (2)	Empty (i.e., no information provided) Information provided: one of the levels of attributes 4 and 5, respectively

Note: [a] Monthly costs are derived from the following CO_2 price levels (per ton of emitted CO_2): 25 €/t; 50 €/t; 100 €/t; 200 €/t; 300 €/t, 500 €/t. See Appendix A1 for details. [b] We vary the CO_2 reduction measure and associated type and level of time, comfort, or monetary costs associated with a possible CO_2 reduction. These are as follows. Changing to public transport: 10 minutes vs. 60 minutes increased daily commuting time. Lower room temperature: still comfortable with normal clothing vs. only comfortable with warm clothing. Switch to small e-car and new heating at home: state subsidies covering most costs vs. must be paid for entirely by the example individual.

The substantive attributes pertain to the following variations: (1) The monthly costs that the example individual must pay due to a certain CO_2 price level. These costs have been derived from price levels ranging from €25 to €500 per ton of emitted CO_2. The underlying calculations use realistic baselines and are described in Appendix A1. (2) Revenue use, i.e. how the public revenues gained by the CO_2 pricing are spent, e.g., for financing climate protection projects or for different payoff schemes in which funds are paid back to the public. (3) The monthly income of the example individual. (4) A CO_2 reduction measure that the example individual can apply to reduce their CO_2 emissions. (5) The time-, comfort-, or money-related costs or effort of the respective measure. We subsume attributes (4) and (5) as the '*behavioral opportunities*' of the example individual to react to CO_2 price burdens by reducing their CO_2 emissions.

The information treatments vary in the following ways: (a) whether they inform the respondent about the general goal of CO_2 pricing or not, (b) whether they provide an anchor or baseline information about typical CO_2 prices or not, and (c) whether they provide information about behavioral opportunities or withhold it (substantive attributes 4 and 5).

Figures 1 and 2 show the introduction screen and an example vignette, respectively. Information that is varied is indicated in square brackets. To facilitate comparison between the information treatments and the empty conditions, content that appears only in the information treatments is additionally highlighted in grey (for illustration purposes only). The example vignette also depicts the three outcome questions on perceived fairness, perceived effectiveness – i.e., the perceived likelihood of behavioral change in the form of CO_2 reduction of the example individual –, and overall policy support. The three outcome questions were presented on separate screens in the online survey. For the last two questions regarding perceived effectiveness and overall policy support, the vignette text was repeated in grey font on a second screen (see Appendix A2 for screenshots of the German original depicting additional example vignettes). This design allowed respondents to view the full vignette while answering each question, even on smaller screens. Since the questions had to be split across multiple screens for this purpose, displaying the vignette in a lighter grey font signaled continuity and clarified that the same scenario was being referenced.

Figure 1: Vignette Introduction Screen

The following section deals with **CO_2 prices**. These are set by policymakers and added to every liter of fuel, natural gas, or heating oil that one purchases. [The aim is to reduce CO_2 emissions and limit climate change.] [empty.]

[Depending on the CO_2 price level, the additional costs for the **average citizen** for driving and heating could be **a few euros**, but also **over 100 euros per month**.] [The additional costs for the **average citizen** for driving and heating are around **10 euros per month** in 2025.] [empty.]

The government revenues from CO_2 pricing could be **paid back to all residents of Germany as an annual relief amount**. If one uses less fuel and natural gas or oil for heating than the average person in Germany, one could actually get back more than one pays for the CO_2 price.

To illustrate the effects of such a CO_2 price, we will now show you a **hypothetical example**. This only refers to the additional costs for **heating and driving**. We are interested in **your personal opinion**.

Notes: Translated from German. Square brackets indicate experimentally varied components, for the information treatments additionally in grey. Boldfaces as in the survey.

Figure 2: Example Vignette and Vignette Outcome Questions

- Mr. Schmidt has a monthly net income of [**€7,000**].
- He generates **average CO_2 emissions** from driving and heating. The CO_2 price would result in **monthly costs of** [**€100**] for this.
- Mr. Schmidt could most effectively **reduce** his CO_2 emissions and thus his costs by investing [several thousand euros] in [a **more economical heating system**].
- [**At the end of the year**, every resident of Germany receives a fixed amount of **€1,200** as **relief** for the CO_2 price. This relief would **completely offset** Mr. Schmidt's **current** monthly CO_2 costs.] [Alternative revenue use: e.g., lower electricity prices.]

Under these circumstances, how fair or unfair do you consider the monthly costs of [€100] that Mr. Schmidt would have to pay for the CO_2 emissions from his car and heating?

You can rate your opinion using numbers between +3 (unfairly high) and −3 (unfairly low).
(answer categories: +3 unfairly high, +2, +1, 0 fair, −1, −2, −3 unfairly low; don't know).

[Figure 2 continued]

How likely is it that Mr. Schmidt will reduce his CO_2 emissions under these conditions?
(answer categories: not at all likely, rather not likely, neither/nor, rather likely, very likely; don't know).

Are you generally for or against the CO_2 pricing regulation shown in the example?
(answer categories: strongly against, rather against, neither/nor, rather in favor, strongly in favor; don't know).

Notes: Translated from German. Square brackets indicate experimentally varied components, for the information treatments additionally in grey. Boldface as in the survey. Each outcome question was presented on a separate screen, repeating the vignette text in grey font for the two latter questions (see Appendix A2 for screenshots).

English translations of the wordings of the text brackets for the experimental attributes "revenue use", "CO_2 reduction measure", and "CO_2 reduction costs" are depicted in Table 2 (see Appendix A3 for the German original). Note that the attributes on CO_2 reduction measures and -costs were not presented to all respondents, while the one on revenue use was. Several further decisions were made regarding the implementation of the experimental treatments and their presentation in the vignettes: the name and gender, as well as the amount of CO_2 emissions ("average") of the example individual ("Mr. Schmidt") were fixed at the same level across all vignettes. Furthermore, the CO_2 emissions referred to in all vignettes were exclusively and explicitly related to driving a car and heating at home, with no mention of any other emission sources. The CO_2 price level was presented as monthly costs in euros, taking an assumed average yearly amount of 2.4 tons of emitted CO_2 for driving and heating as a basis and multiplying this amount by the respective and varied price-per-ton of emitted CO_2 (range from 25 €/t to 500 €/t) divided by 12. We chose presenting monthly expenditures for these ongoing costs because these are assumed to be easier to evaluate and set into relation to other monthly amounts of money, such as rents, heating, and electricity bills, as well as salaries, which are all usually transferred on a monthly basis in Germany. For the 100 percent and 50 percent payoff conditions for revenue use, in turn, we chose presenting yearly amounts for two reasons: firstly to precise and restrict the first outcome question on perceived fairness to the initial monthly costs induced by CO_2 pricing and hence avoid confusion; and secondly because the ongoing debate on revenue recycling

policies in Germany ("Klimageld") at the time of the survey envisaged yearly payoffs, making reporting yearly payoff figures more close to reality.

Table 2: Wordings for Attributes "Revenue Use", "CO_2 Reduction Measure", and CO_2 Reduction Costs"

Attribute	Wording
CO_2 reduction measure and CO_2 reduction costs	[Mr. Schmidt could most effectively **reduce** his CO_2 emissions and thus his costs by...]
	...**taking the bus or train more often instead of driving his car**. This would mean adding about **10 minutes** to his daily commute. ...**taking the bus or train more often instead of driving his car**. This would mean adding about **60 minutes** to his daily commute.
	...**heating his home less** than he has been doing. With normal clothing, it would still be comfortable. ...**heating his home less** than he has been doing. Wearing warm clothing would be the only way to remain comfortable.
	...**switching from his powerful gasoline-powered car to a more economical electric car**. A large part of the purchase costs would be **covered by government subsidies**. ...**switching from his powerful gasoline-powered car to a more economical electric car**. He would have to **pay the full purchase price himself**.
	...taking advantage of **government subsidies** for a **more economical heating system**, which would cover a large part of the conversion costs. ...investing several thousand euros in a **more economical heating system**.
Revenue use	**At the end of the year**, every resident of Germany receives a fixed amount of **€ [monthly costs × 12]** as **relief** for the CO_2 price. This relief would **completely offset** Mr. Schmidt's **current** monthly CO_2 costs.
	At the end of the year, every resident of Germany receives a fixed amount of **€ [monthly costs × 12/2]** as **relief** for the CO_2 price. This relief would **offset half of** Mr. Schmidt's **current** monthly CO_2 costs.
	Government revenue from the CO_2 price will be paid out to **low-income households**.
	Government revenue from the CO_2 price will be used to **reduce electricity prices for all citizens and companies**.
	Government revenue from the CO_2 price will be used to **reduce electricity prices for all companies**.
	Government revenue from the CO_2 price is used to **finance climate protection projects**.

Notes: Translated from German. Boldface as in the survey (see Appendix A3 for the German original).

As a side note, it should be mentioned that several additional conventional survey questions were posed directly after the FSE in the GLEN Inter-wave survey. These concern a self-reported estimate of how well respondents feel informed about CO_2 pricing in general, a subjective perception of the overall efficacy of CO_2 pricing, a question on second-order beliefs regarding public support for CO_2 pricing in the German population, and a six-item battery on support for different revenue use policies. Documentation for these additional questions can be accessed in the regular GLEN data releases and the accompanying material. Of further note, the regular GLEN panel questionnaire program contains more questions on support for CO_2 pricing (as well as other climate policies), which are fielded in other survey waves.

2.2 Technical Setup of the FSE: Vignette Sample and Additional Sample Splits

The experimental treatments presented in the previous section were incorporated in two ways. Firstly, a multifactorial core selected treatment combinations using a *D*-efficient, purposive sampling technique (Auspurg & Hinz, 2015; Dülmer, 2016; Kuhfeld, 2010). Secondly, six conventional random sample splits were used, providing different amounts of information to survey respondents based on the information treatment conditions. Table 3 gives an overview of this setup. The multifactorial, *D*-efficient core comprises the main substantial treatments on attributes of the policy design and the fictitious example individual, plus one of the three information treatments (information on the general aim of CO_2 pricing). The information treatments on anchor CO_2 price and behavioral opportunities (presenting or not the attributes on CO_2 reduction measure and costs) were assigned using conventional sample splits. The reasons for that combination of sampling techniques are explained below. We will first describe the *D*-efficient multifactorial core and afterwards the six random sample splits.

Out of the full factorial of $K = 2{,}304$ vignettes[2], we drew a *D*-efficient subsample of $k = 720$ vignettes with $D = 92.2$ (using the macros provided by Kuhfeld, 2010, for the

[2] The full factorial is the Cartesian product of the number of levels of all experimental attributes in the multifactorial core, i.e., $K = 6 \times 6 \times 4 \times 4 \times 2 \times 2 = 2{,}304$ combinations.

SAS software).[3] The algorithm optimizes orthogonality and level balance of the attributes. We chose a resolution V design that ensures that at least all main effects, all two-way interactions, as well as six specific three-way and one four-way interactions are orthogonalized.[4] Appendix A5 provides information on additional technical aspects of this setup (balance of the attribute levels and correlations between attributes). In each experimental sample split (see below), respondents were randomly allocated to one out of the 720 vignettes.[5]

Table 3: Experimental Information Treatment Groups

Attribute	**Split 1 10 %**	**Split 2 10 %**	**Split 3 30 %**	**Split 4 10 %**	**Split 5 10 %**	**Split 6 30 %**
Multifactorial core:						
Monthly costs due to CO_2 pricing (6)	☑	☑	☑	☑	☑	☑
Revenue use (6)	☑	☑	☑	☑	☑	☑
Monthly net income of example indiv. (4)	☑	☑	☑	☑	☑	☑
CO_2 reduction measure (4)	☑	☑	☑			
CO_2 reduction costs (2)	☑	☑	☑			
Info treatment: aim of CO_2 pricing (2)	☑	☑	☑	☑	☑	☑
Additional information treatment splits:						
Info on anchor CO_2 price: 10 € in 2025		☑			☑	
Info on anchor CO_2 price: few € to >100 €			☑			☑

Notes: Percentage values indicate the relative size of the assigned subsample. Number in brackets depict number of levels.

We next outline the six random sample splits that vary two of our information treatments (see again Table 3 for an overview). Before being assigned to a unique vignette containing the multifactorial core, respondents were randomly split into one of the six

[3] The SAS code is shown in Appendix A4.
[4] Orthogonalized by design are the three-way interactions income × monthly CO_2 costs × revenue use; income × monthly CO_2 costs × CO_2 reduction measure; income × monthly CO_2 costs × CO_2 reduction costs; income × CO_2 reduction measure × CO_2 reduction costs; monthly CO_2 costs × CO_2 reduction measure × CO_2 reduction costs; revenue use × CO_2 reduction measure × CO_2 reduction costs; and the four-way interaction income × monthly CO_2 costs × CO_2 reduction measure × CO_2 reduction costs.
[5] Using a block structure, we optimized the balance of evaluations per stimulus. Only after all 720 vignettes had been evaluated did the survey software use the next block of 720 vignettes.

experimental information treatment groups. These groups varied the provision of information on anchor CO_2 prices (three levels: no information vs. two different anchors, see Table 1) and on behavioral opportunities for emission reduction (two levels: information vs. no information). Crossing these factors resulted in a 3 × 2 factorial design.[6] Groups 1 through 3 receive the information on behavioral opportunities (two vignette attributes), while groups 4 through 5 do not. Groups 1 and 4 do not receive information on anchor/typical CO_2 prices. Groups 2 and 5 are informed that "the additional costs for the average citizen for driving and heating are around 10 euros per month in 2025", and groups 3 and 6 are informed that "depending on the CO_2 price level, the additional costs for the average citizen for driving and heating could be a few euros, but also over 100 euros per month". Splitting the sample into these six different groups allowed us to vary the number of respondents assigned to each condition.

As the anchor information treatments primarily serve a methodological purpose, the intended sample sizes for the "no information" and "10 euros in 2025" groups are smaller than that of the "few euros…over 100 euros" group. 10 percent of respondents, respectively, have been assigned to groups 1, 2, 4, and 5 in each case, and 30 percent, respectively, to groups 3 and 6.

The reasons for combining a *D*-efficient multifactorial core with simple random splits were as follows. Basically, it would have been desirable to incorporate all experimental treatments in a *D*-efficient design because this increases power to detect possible effects of experimental variables by setting factors and their interactions orthogonally and by maximizing variance through improving level balance (all levels occur with about the same frequency). However, the information treatment on baseline/anchor information primarily addresses a secondary methodological question. For this reason, we opted for smaller sample sizes for two levels and oversampled one level to ensure constant anchor information for most respondents. Additionally, integrating the information treatment on CO_2 reduction measures and -costs simultaneously in the *D*-efficient core would require dealing with implausible combinations in the design, because providing information on reduction cost levels also requires providing information on

[6] For technical reasons related to the survey software, a 10-group random split was actually used to picture the six experimental groups. See Sections 3 and 4 for information on this.

type of reduction measures. Technical solutions to this issue would undermine the efficiency, and thus one major advantage, of *D*-efficient sampling for the multifactorial core. Therefore, we decided to increase power for the core research questions, where we also expect more interactions between different treatments. Note, however, that both strategies – the *D*-efficient selection and random variation – ensure a key aspect of experiments: the random allocation of treatment conditions (and their combinations) to respondents. Additionally, both techniques ensure the uncorrelatedness of the key treatment effects (and we checked correlation structures before fielding the survey). The only difference is that there is greater efficiency (power) in estimating the (moderator) effects of treatments included in the experimental core.

3 GLEN Survey Implementation

The FSE on CO_2 pricing was implemented in Inter-wave survey 2025a of GLEN. Inter-wave surveys are short surveys within the GLEN survey program, conducted between the regular panel waves of GLEN. While the GLEN panel core also includes paper-and-pencil (PAPI) questionnaires once a year, the survey mode for the Inter-wave surveys is online exclusively and invitations are sent out via email. All GLEN online surveys are optimized for different input devices, i.e., desktop computers, smartphones, and tablets. Respondents received an incentive of 3 euros for completing the survey.

Field phase started on September 17, 2025, and lasted until October 23, 2025. One reminder was sent out to respondents on October 6, 2025. For more information on technical aspects and fielding of the Inter-wave survey 2025a, please refer to Schmiedeberg, Königer, and Emmer (2026). The survey was conducted using the SoSci survey software (Leiner, 2025). N = 14,960 online panelists were invited to the Inter-wave survey (corresponding to 90 percent of the available gross online sample at the time of the survey), of which a random subsample of 90 percent was set to be assigned to the FSE on CO_2 pricing.[7] In total, N = 8,335 respondents participated in the Inter-wave survey. N = 7,478 respondents were randomly assigned to the FSE on CO_2

[7] These two 90 percent random subsamples are used for methodological research on panel attrition and conditioning and are not further addressed in this technical report.

pricing, and N = 7,408 (99 percent) answered the first outcome question on perceived fairness of the pricing scenario in the vignette (including those who responded "don't know"). Table 4 provides an overview of the sample sizes available for the three outcome questions. Dropouts (i.e., break-offs) and item-nonresponse throughout the FSE are negligible; 98.8 percent of respondents assigned to the module provided valid answers to the third outcome question (including "don't know"); 98.4 percent to all three outcome questions. The FSE procedure did not seem to burden the heterogeneous group of GLEN respondents too much, which is a desirable outcome in terms of avoiding selective responses, for example.

Table 4: Sample Sizes by Experimental Splits and Outcome Questions

	Split 1	**Split 2**	**Split 3**	**Split 4**	**Split 5**	**Split 6**	**Total**
Outcome 1: prcvd. fairness	740	744	2,220	742	741	2,221	7,408
Outcome 2: prcvd. effectiveness	741	745	2,215	740	740	2,221	7,402
Outcome 3: support	739	742	2,217	740	742	2,212	7,392
Total *N* assigned to split	749	748	2,242	748	749	2,242	7,478

Note: Indicated in the middle three rows are absolute numbers of valid cases including "don't know" answers for the three outcome questions.

The empirical representation of the multifactorial core of the FSE in the data, i.e., the empirical balance of attribute levels and correlations of the attributes, is reported in Appendix A6. The intended experimental setup is very well reflected in the data.

Table 5 reports descriptive statistics for the three outcome variables of the FSE; distributional plots are depicted in Appendix A7. The data show that all response categories are filled and that the variables show considerable variance. However, few respondents choose category 5 ("very likely") for outcome 2 (perceived effectiveness), indicating that very few respondents think that the CO_2 pricing scheme depicted in the respective vignette induces a behavioral change (emission reduction).

Table 5: Descriptive Statistics of the FSE Outcome Variables

	N	% don't know	Min/ Max	Mean	SD	Median	P25/ P75
Outc. 1: fairness	7,408	12.7	−3/3	0.349	1.657	0	0/2
Outc. 2: effectiveness	7,402	6.7	1/5	2.009	0.910	2	1/2
Outc. 3: support	7,392	8.9	1/5	2.736	1.178	3	2/4

Note: N *includes "don't know" answers, the summary statistics do not. "*P25/P75*" refers to the 25-/75-percent percentiles, respectively. Outcome 1 has been recoded to the values depicted in the survey question.*

4 Data Structure

The FSE data are released in a separate file ("04_interwave_2025a_vig") in the release package. Data users who want to merge the FSE data with GLEN datafiles can use the respondent-identifier variable `id` and the survey identifier `survey`. Using the FSE data requires no special data preparation actions (such as reshaping to long format), because respondents answered only one vignette each. This also implies that the data do not have a hierarchical multilevel structure; hence analysis of the FSE data does not necessitate accounting for respondent-level clustering.

Table 6 gives an overview of the variables in the dataset. Note that the order of the variables follows the sequence in the survey and not the content-related ordering presented above in this technical report. Variable `vig2split1` contains the random sample splits assigning each respondent to one of the six experimental information treatment groups. For technical reasons related to the survey software, a 10-group random split was actually used to picture the six experimental groups. Hence, codes 3, 4, 5 capture experimental group 3 and codes 8, 9, 10 capture experimental group 6 (see Table 3). Variable `vig2id` contains the unique vignette number drawn for each respondent. Variables with stubs `vig2dim` designate the experimental attributes in the multifactorial core, and variables with stubs `vig2q` contain the data on the three outcome questions of the FSE. Note that `vig2q1` (perceived fairness) is coded with values 1 to 7 in the data, while the original survey question presented a value range from +3 ("unfairly high") over 0 ("fair") to −3 ("unfairly low") to respondents. To allow data users to

incorporate response latencies into their analyses, four variables on these are part of the data as well; they depict, for each separate survey screen, the time in seconds elapsed between landing on the respective screen and clicking the "next" button to proceed to the next screen. Variable `vig2introlat` contains response latencies for the vignette intro screen, and `vig2q*lat` those for each of the three vignette outcome questions (with "`*`" referring to the number of outcome question).

Any use of these data should be accompanied by a citation of this technical report as well as the Release-DOI of the GLEN dataset (GLEN, 2026).

Table 6: Variables in the Dataset

Variable Name	Variable Label	Categories (Code, Label)
id	Respondent identification number	
survey	Survey indicator	4 Inter-wave 2025a
vig2split1	Vignette study carbon price: exp. between splits	-33 Break-Off -3 Does not apply (filtered out) 1 Anchor empty, w/ beh. opp. 2 Anchor 2025, w/ beh. opp. 3 Anchor 10...100€, w/ beh. opp. 4 Anchor 10...100€, w/ beh. opp. 5 Anchor 10...100€, w/ beh. opp. 6 Anchor empty, w/o beh. opp. 7 Anchor 2025, w/o beh. opp. 8 Anchor 10...100€, w/o beh. opp. 9 Anchor 10...100€, w/o beh. opp. 10 Anchor 10...100€, w/o beh. opp.
vig2id	Vignette study carbon price: vignette id	-33 Break-Off -3 Does not apply (filtered out) Values [1...720] without labels
vig2introlat	Vignette study carbon price: response latency for vignette intro screen	-33 Break-Off -3 Does not apply (filtered out) Other values without labels
vig2dim1	Vignette study carbon price: info aim co2 pricing	-33 Break-Off -3 Does not apply (filtered out) 1 Empty/no info 2 Info given: aim co2 pricing
vig2dim2	Vignette study carbon price: income example person	-33 Break-Off -3 Does not apply (filtered out) 1 1,500 € 2 2,500 € 3 4,200 € 4 7,000 €

[Table 6 continued]

vig2dim3	Vignette study carbon price: co2 price costs	-33	Break-Off
		-3	Does not apply (filtered out)
		1	5 €/month (25 €/t)
		2	10 €/month (50 €/t)
		3	20 €/month (100 €/t)
		4	40 €/month (200 €/t)
		5	60 €/month (300 €/t)
		6	100 €/month (500 €/t)
vig2dim4	Vignette study carbon price: co2 reduction measure	-33	Break-Off
		-3	Does not apply (filtered out)
		1	Public transport
		2	Room temperature
		3	E-car
		4	New heating at home
		5	Empty/no info
vig2dim5	Vignette study carbon price: co2 reduction costs	-33	Break-Off
		-3	Does not apply (filtered out)
		1	Low costs
		2	High costs
		3	Empty/no info
vig2dim6	Vignette study carbon price: revenue use	-33	Break-Off
		-3	Does not apply (filtered out)
		1	100% payoff
		2	50% payoff
		3	Low-inc households
		4	All: lower energy costs
		5	Companies: lower energy costs
		6	Clim. protect. projects
vig2q1	Vignette study carbon price: fairness of the individual carbon price	-33	Break-Off
		-3	Does not apply (filtered out)
		-2	No answer
		-1	Don’t know
		1	Unfairly high (+3)
		2	(+2)
		3	(+1)
		4	Fair (0)
		5	(-1)
		6	(-2)
		7	Unfairly low (-3)
vig2q1lat	Vignette study carbon price: response latency for fairness question	-33	Break-Off
		-3	Does not apply (filtered out)
		Other values without labels	
vig2q2	Vignette study carbon price: emission reduction due to carbon price expected	-33	Break-Off
		-3	Does not apply (filtered out)
		-2	No answer
		-1	Don’t know
		1	Not at all likely
		2	Rather not likely
		3	Neither, nor
		4	Rather likely
		5	Very likely
vig2q2lat	Vignette study carbon price: response latency for emission reduction question	-33	Break-Off
		-3	Does not apply (filtered out)
		Other values without labels	

[Table 6 continued]			
vig2q3	Vignette study carbon price: support of carbon price as described	-33 -3 -2 -1 1 2 3 4 5	Break-Off Does not apply (filtered out) No answer Don't know Strongly against Rather against Neither, nor Rather in favor Strongly in favor
vig2q3lat	Vignette study carbon price: response latency for support question	-33 -3 Other values without labels	Break-Off Does not apply (filtered out)

Note: The category –3 ("does not apply (filtered out)") refers to the random 10 percent subsample that was not assigned to the FSE on CO_2 pricing. This experimental split could be used for analyses on panel attrition and conditioning.

Acknowledgements

We would like to thank the whole GLEN team for comments and recommendations regarding the design of this module, Tessa Schick, Claudia Schmiedeberg, and Theo Wiesholler for revising this technical report, and Lola Möding as well as Theo Wiesholler for their help in conducting several pretests.

Appendix

A1: Calculation of Monthly CO_2 Costs and Yearly Payoff Amounts Reported in the Vignettes

The core of the survey experiment involves experimentally varying CO_2 prices and presenting their consequences for the individuals sketched in the scenarios. CO_2 prices are typically measured in euros per ton of emitted CO_2, an abstract unit that is not commonly used or understood by the average consumer. We therefore converted the prices into figures that survey respondents would find easier to understand (we ran cognitive pre-tests to check this). Another prerequisite in designing the setup was that all calculation figures must – at least to a certain degree – be realistic while ensuring that the vignette levels have enough variance.

Several decisions were made in this regard. First, to reduce complexity, all reported CO_2 emissions refer to those stemming from motoring and heating only. Second, costs resulting from different CO_2 price levels are presented as monthly amounts, which is assumed to make it easier for respondents to comprehend and evaluate the figures. In turn, rebate amounts are presented as yearly payments in order to avoid confusion and because this is the actual policy scheme discussed in Germany at the time of the survey. Third and based on insights from a pretest study, we decided to set the CO_2 emissions of the fictitious example person at the average level for heating and motoring. We chose an average of 2.4 tons of CO_2 emitted per year.[8] This value is multiplied by the respective carbon price per ton and divided by 12 to yield monthly costs. Regarding the rebate amounts in the 100 percent and 50 percent payoff conditions of "revenue use," we

[8] The calculation is as follows: For driving a petrol engine car and assuming a consumption of 6 l/100km, driving 600 km per month (this being a rough approximation as statistics on this are difficult to retrieve, cf. https://www.dat.de/news/jahresfahrleistung/), and 2.37 kg of CO_2 emissions per liter of petrol (https://www.helmholtz.de/newsroom/artikel/wie-viel-co2-steckt-in-einem-liter-benzin/), one arrives at yearly CO_2 emissions of about 1 ton. For gas heating, the average CO_2 emissions estimation are calculated by assuming 150 kWh (https://www.finanztip.de/co2-steuer/) times 0.2 kg CO_2 emissions (https://www.verbraucherzentrale.de/wissen/energie/heizen-und-warmwasser/klimapaket-hier-berechnen-sie-den-co2preis-ihrer-heizkosten-43806) times 47.5 m² average living surface per capita in Germany (https://www.umweltbundesamt.de/daten/private-haushalte-konsum/wohnen/wohnflaeche), yielding 1.4 tons of average yearly CO_2 emissions. Summing up these figures for driving and heating yields an estimation of 2.4 t of CO_2 emissions per year.

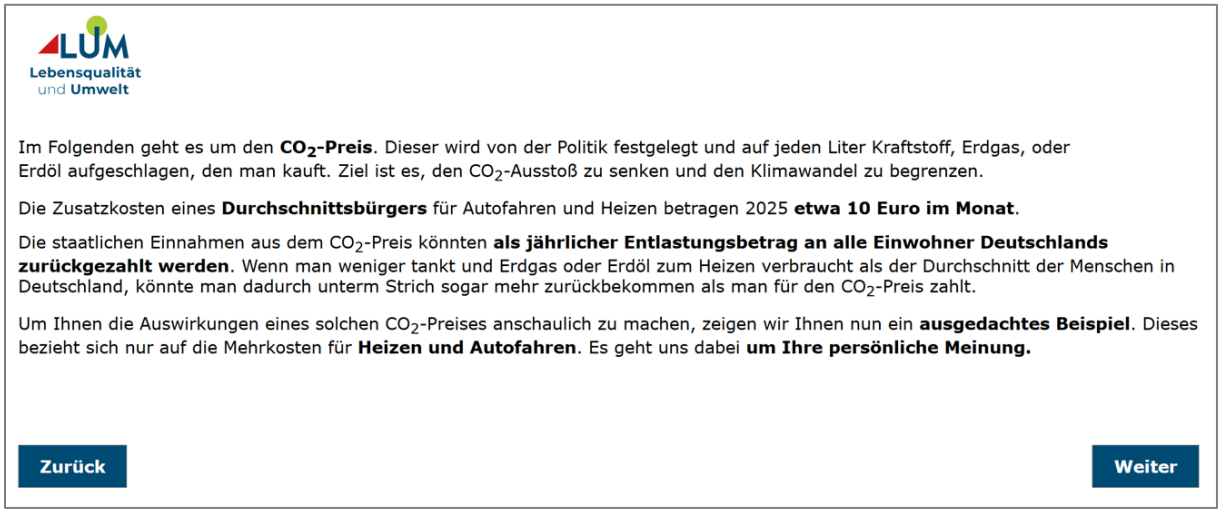
reported yearly amounts, i.e., monthly costs multiplied by 12 or 12/2, respectively. Table A1 gives an overview of the figures presented to survey respondents in the vignettes.

Table A1: Monthly CO_2 Costs and Yearly Payoff Amounts Presented in the Vignettes

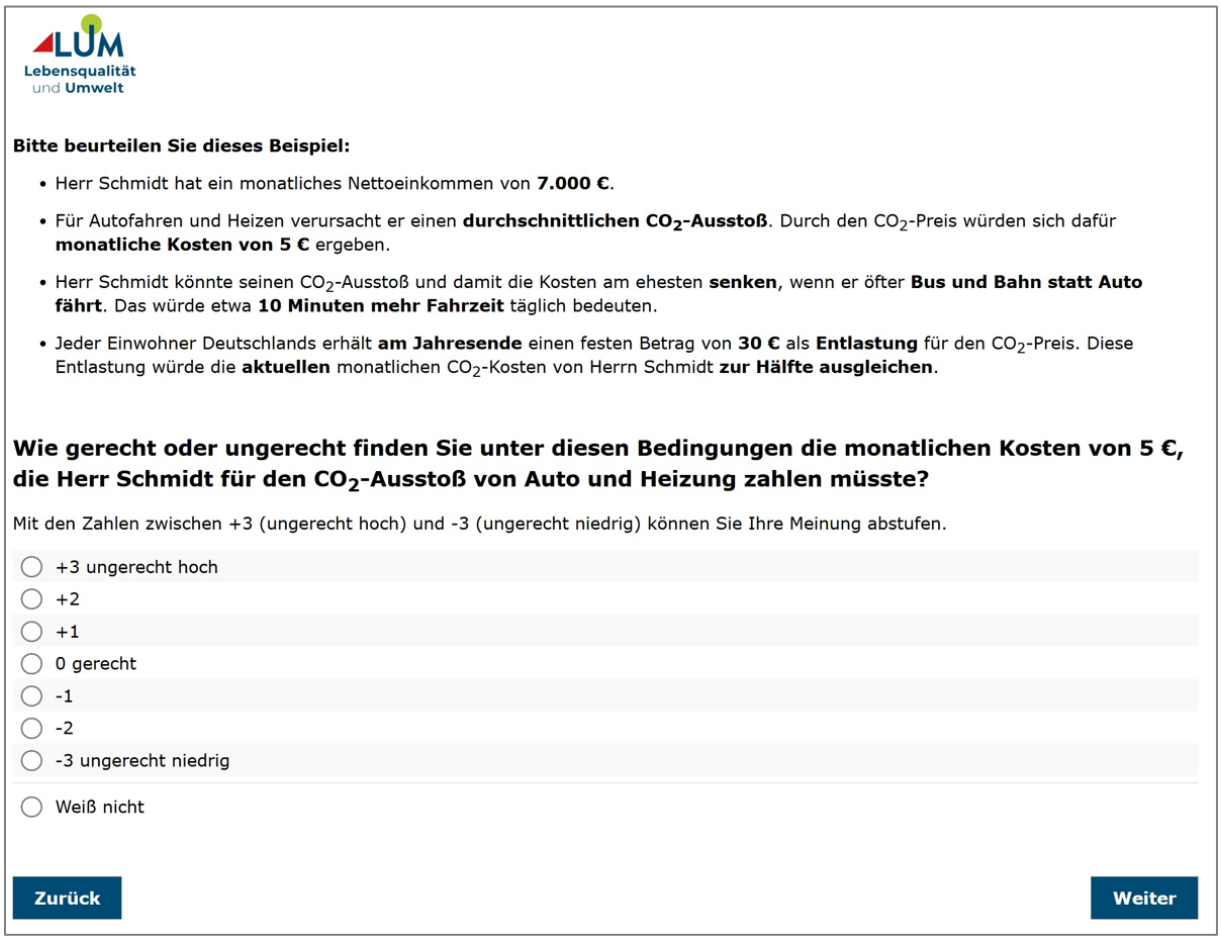
CO_2 Price, €/t	**Monthly CO_2 Costs, €**	**Yearly Payback, 100 % Payoff, €**	**Yearly Payback, 50 % Payoff, €**
25	5	60	30
50	10	120	60
100	20	240	120
200	40	480	240
300	60	720	360
500	100	1200	600

A2: Screenshots of Example Vignettes (German Original)

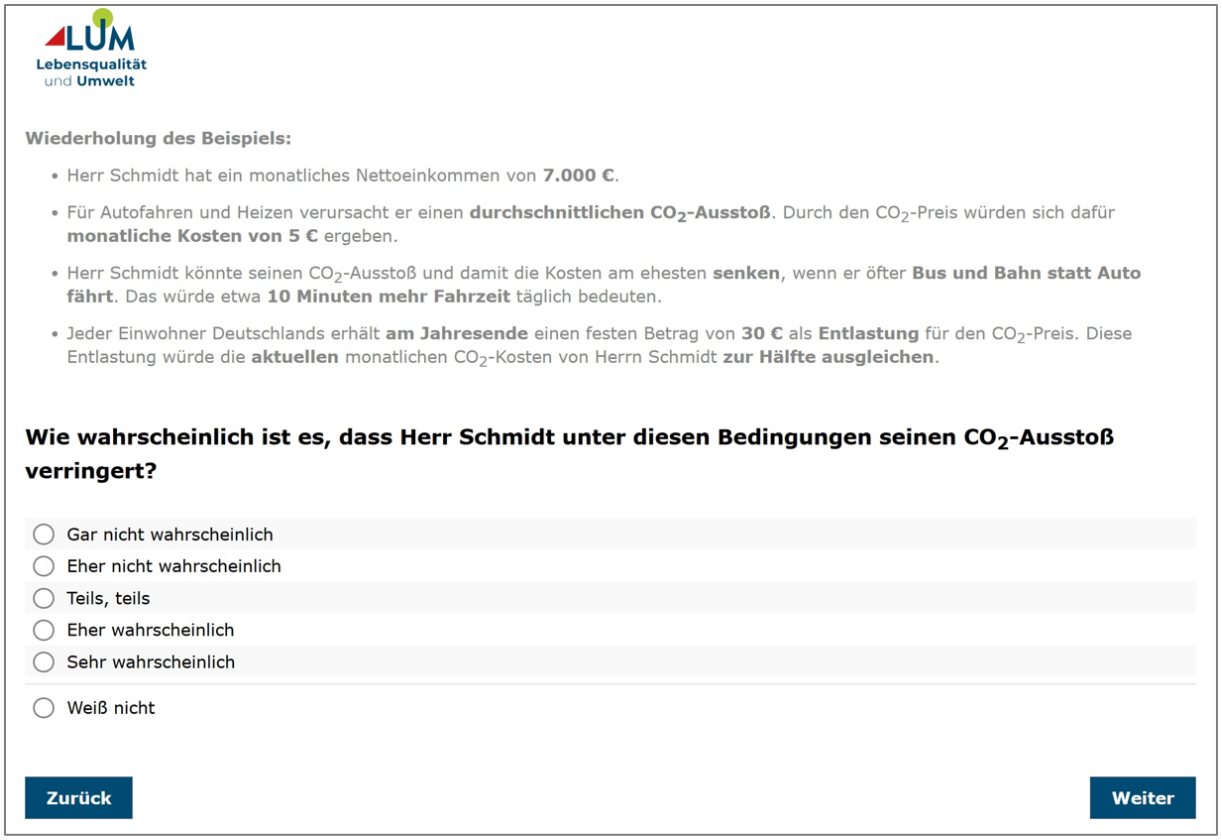
Vignette Introduction Screen:



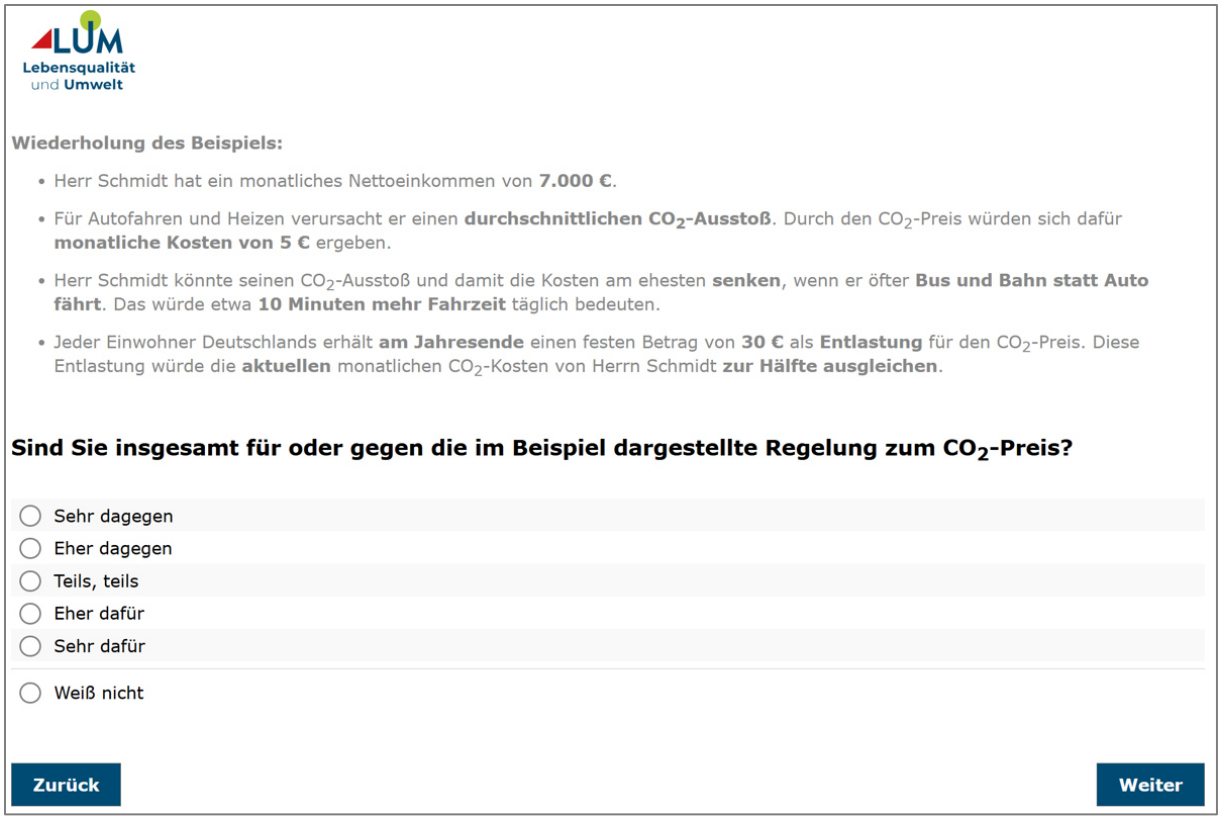
Vignette Screen 1:



Vignette Screen 2:



Vignette Screen 3:



A3: Wordings for Attributes "Revenue Use", "CO_2 Reduction Measure", and CO_2 Reduction Costs" (German Original)

Table A3: Wordings for Attributes "Revenue Use", "CO_2 Reduction Measure", and CO_2 Reduction Costs" (German Original)

Attribute	German Wording
CO_2 reduction measure and CO_2 reduction costs	[Herr Schmidt könnte seinen CO_2-Ausstoß und damit die Kosten am ehesten **senken**, wenn er…]
	…öfter **Bus und Bahn statt Auto fährt**. Das würde etwa **10 Minuten mehr Fahrzeit** täglich bedeuten. …öfter **Bus und Bahn statt Auto fährt**. Das würde etwa **60 Minuten mehr Fahrzeit** täglich bedeuten.
	…seine Wohnung **weniger warm heizt** als bisher. Mit normaler Kleidung wäre es dann noch angenehm. …seine Wohnung **weniger warm heizt** als bisher. Nur mit warmer Kleidung wäre es dann noch angenehm.
	…von seinem **stark motorisierten Benziner auf ein sparsameres E-Auto umsteigt**. Ein großer Teil der Anschaffungskosten würde durch **staatliche Förderung abgedeckt**. …von seinem **stark motorisierten Benziner auf ein sparsameres E-Auto umsteigt**. Die Anschaffungskosten muss er **vollständig selbst bezahlen**.
	…**staatliche Förderung** für eine **sparsamere Heizung** nutzt, die einen großen Teil der Umbaukosten deckt. …mehrere Tausend Euro in eine **sparsamere Heizung** investiert.
Revenue use	Jeder Einwohner Deutschlands erhält **am Jahresende** einen festen Betrag von **[MONATSKOSTEN * 12] €** als **Entlastung** für den CO_2-Preis. Diese Entlastung würde die **aktuellen** monatlichen CO_2-Kosten von Herr Schmidt **vollständig ausgleichen**.
	Jeder Einwohner Deutschlands erhält **am Jahresende** einen festen Betrag von **[(MONATSKOSTEN * 12)/2] €** als **Entlastung** für den CO_2-Preis. Diese Entlastung würde die aktuellen monatlichen CO_2-Kosten von Herr Schmidt **zur Hälfte ausgleichen**.
	Die staatlichen Einnahmen aus dem CO_2-Preis werden an **Haushalte mit niedrigem Einkommen** ausgezahlt.
	Die staatlichen Einnahmen aus dem CO_2-Preis werden für eine **Absenkung der Strompreise für alle Bürger und Unternehmen** genutzt.
	Die staatlichen Einnahmen aus dem CO_2-Preis werden für eine **Absenkung der Strompreise für alle Unternehmen** genutzt.
	Die staatlichen Einnahmen aus dem CO_2-Preis werden für die **Finanzierung von Klimaschutzprojekten** genutzt.

[Table A3 continued]	
Anchor CO_2 price	[Empty (i.e., no information given)]
	Die Zusatzkosten eines **Durchschnittsbürgers** für Autofahren und Heizen betragen 2025 **etwa 10 Euro im Monat**. Die Zusatzkosten eines **Durchschnittsbürgers** für Autofahren und Heizen könnten je nach Höhe des CO_2-Preises **wenige Euro**, aber auch **über 100 Euro pro Monat** betragen.

Notes: Boldface as in the survey.

A4: SAS Code for *D*-Efficient Multifactorial Core

```
%mktex (2 4 6 6 4 2, interact=1|2|3|4|5|6@2 2*3*4 2*3*5 2*3*6
2*5*6 3*5*6 4*5*6 2*3*5*6, n=720, seed=815);
```

Note: In this code, the numbers appearing first in the bracket depict the number of levels of the six attributes and represent the following attributes: x1 aim of CO_2 pricing (2 levels), x2 income of example individual (4 levels), x3 monthly costs due to CO_2 pricing (6 levels), x4 revenue use (6 levels), x5 CO_2 reduction measure (4 levels), x6 CO_2 reduction costs (2 levels). The remaining figures on interactions refer to the respective attribute x1–x6. This entails that the first three-way interaction orthogonalized refers to x2 × x3 × x4, meaning income × monthly costs × revenue use.

A5: Further Design Aspects of the Multifactorial Experimental Core

Table A5a: Balance of Experimental Attribute Levels in the Design Matrix

Nr.	Attribute	Levels	Freq.
1	Monthly costs due to CO_2 pricing	5 € 10 € 20 € 40 € 60 € 100 €	120 120 120 120 120 120
2	Revenue use	100 percent payoff per-capita 50 percent payoff per-capita Payoff to low-income households Lower electricity prices for all citizens and companies Lower electricity prices for all companies Financing of climate-protection projects	120 120 120 120 120 120
3	Monthly net income of example individual	1,500 € 2,500 € 4,200 € 7,000 €	180 180 180 180
4	CO_2 reduction measure	Use public transport Lower room temperature Switch from high-powered petrol to smaller e-car Install new heating at home	180 179 180 181
5	CO_2 reduction costs	Low High	363 357
6	Aim of CO_2 pricing	Empty (i.e., no information provided) Information provided	364 356

Table A5b: Correlation Matrix of Experimental Attributes in the Design Matrix

		1	2	3	4	5
1	Monthly costs due to CO_2 pricing					
2	Revenue use	0.000				
3	Monthly net income of example individual	0.000	0.000			
4	CO_2 reduction measure	0.011	0.002	0.007		
5	CO_2 reduction costs	−0.009	−0.004	−0.004	0.004	
6	Info treatment: aim of CO_2 pricing	−0.008	−0.008	0.008	−0.007	0.003

Notes: Spearman correlations. N = *720.*

A6: Experimental Design Checks: Empirical Balance and Correlations

Table A6a: Empirical Balance of Experimental Attribute Levels in the Data

Nr.	Attribute	Levels	Freq.	%
1	Monthly costs due to CO_2 pricing	5 €	1,250	16.7
		10 €	1,239	16.6
		20 €	1,244	16.6
		40 €	1,253	16.8
		60 €	1,252	16.7
		100 €	1,240	16.6
2	Revenue use	100 percent payoff per-capita	1,247	16.7
		50 percent payoff per-capita	1,248	16.7
		Payoff to low-income households	1,252	16.7
		Lower electricity prices for all citizens and comp.	1,237	16.5
		Lower electricity prices for all companies	1,239	16.6
		Financing of climate-protection projects	1,255	16.8
3	Monthly net income of example individual	1,500 €	1,881	25.2
		2,500 €	1,865	24.9
		4,200 €	1,862	24.9
		7,000 €	1,870	25.0
4	CO_2 reduction measure	Use public transport	937	25.1
		Lower room temperature	933	25.0
		Switch from high-powered petrol to smaller e-car	930	24.9
		Install new heating at home	939	25.1
5	CO_2 reduction costs	Low	1,890	50.6
		High	1,849	49.5
6	Aim of CO_2 pricing	Empty (i.e., no information provided)	3,772	50.4
		Information provided	3,706	49.6

Table A6b: Empirical Correlation Matrix of Experimental Attributes in the Data

		1	2	3	4	5
1	Monthly costs due to CO_2 pricing					
2	Revenue use	0.001 (0.961)				
3	Monthly net income of example individual	0.003 (0.795)	0.001 (0.904)			
4	CO_2 reduction measure	0.011 (0.520)	0.003 (0.859)	0.005 (0.752)		
5	CO_2 reduction costs	−0.013 (0.426)	−0.007 (0.671)	−0.000 (0.980)	0.006 (0.731)	
6	Info treatment: aim of CO_2 pricing	−0.008 (0.469)	−0.008 (0.486)	0.005 (0.666)	−0.012 (0.479)	−0.003 (0.880)

Notes: Spearman correlations, p-values in parentheses. N = *7,478 for correlations not involving attributes 4 and 5, and* N = *3,739 for correlations involving attributes 4 and 5.*

A7: Distributional Plots of FSE Outcome Variables

Figure A7a: Distribution of Outcome Variable 1 (Perceived Fairness)

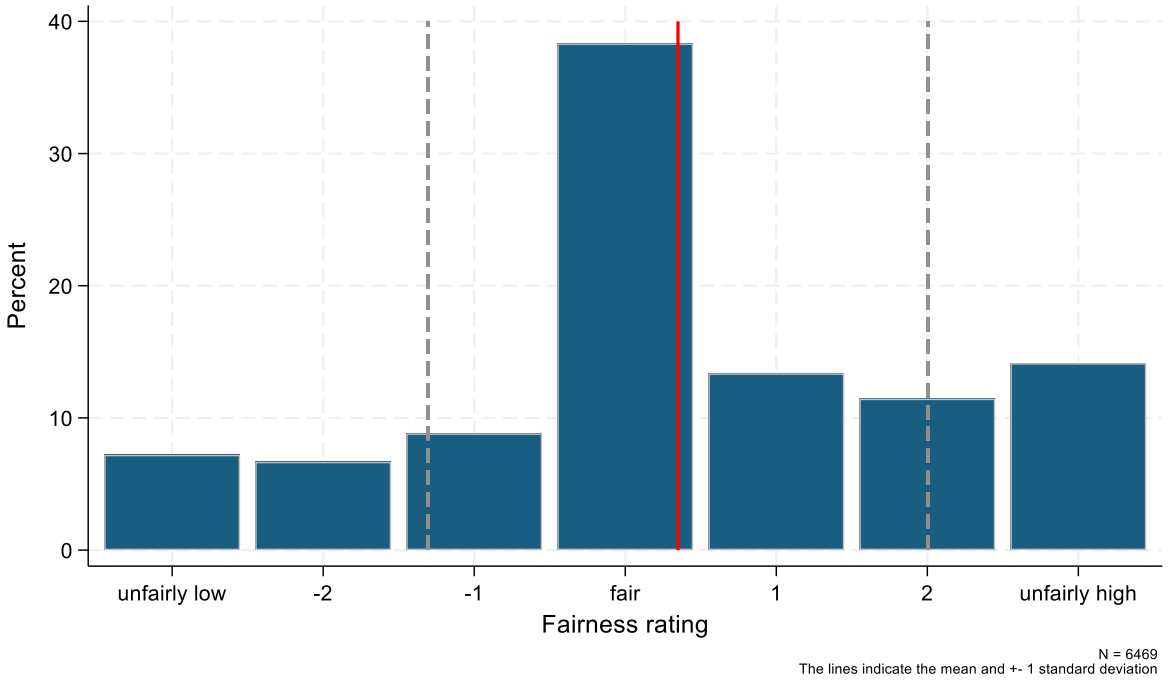


Figure A7b: Distribution of Outcome Variable 2 (Perceived Effectiveness)

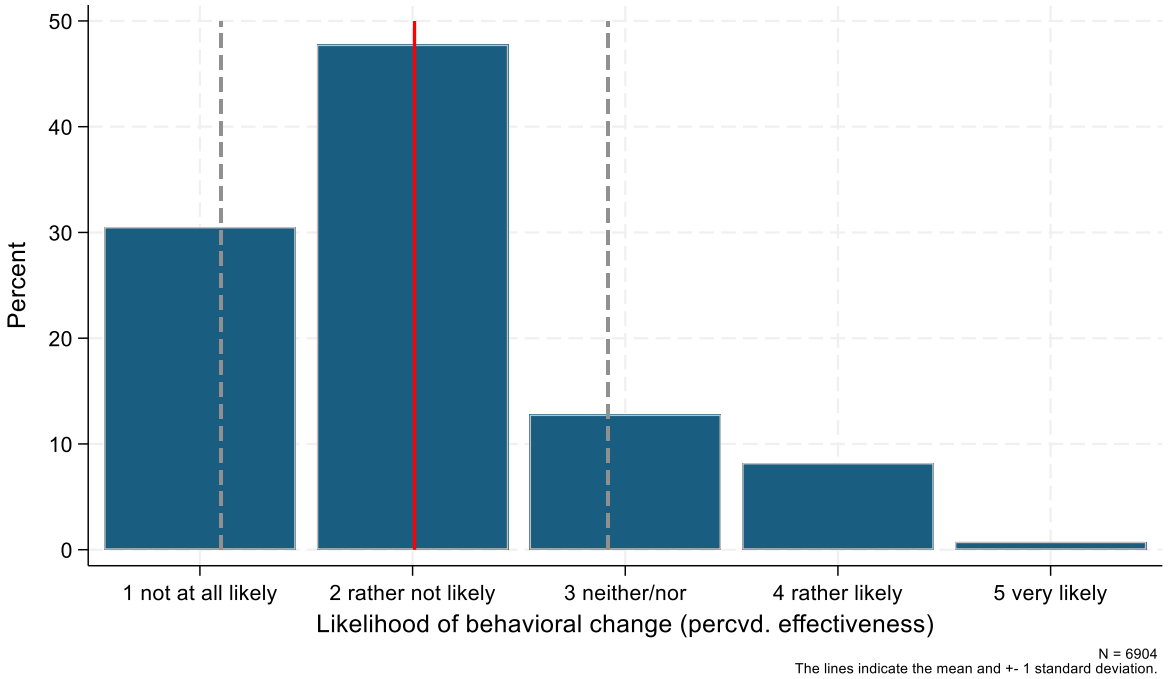
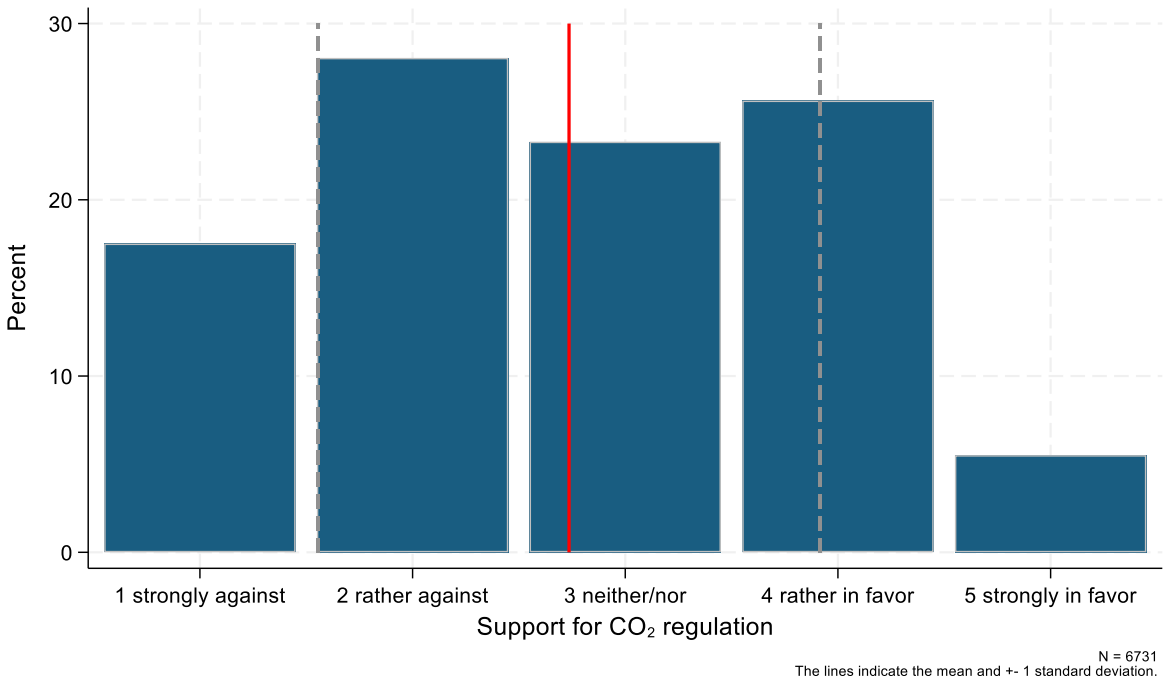


Figure A7c: Distribution of Outcome Variable 3 (Overall Support)



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