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Mode Choice for Leisure Travel in Europe: Simulating Future Transport Policies*

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Abstract

The European travel sector is experiencing a transformation driven by increased climate awareness and policy measures aimed at reducing external costs such as emissions. This study examines how Swiss travelers respond to these developments, using a stated preference experiment including the modes train, night train, car, and airplane. Employing nested logit models, we find a significant willingness-to-pay for sustainable aviation fuel (SAF) of CHF 94 per ton of CO_2e. Based on the estimated coefficients, we evaluate the impacts of four policy scenarios: an aviation tax (CHF 30), a night train subsidy (CHF 20), a SAF blending quota, and a market outlook for 2030. These scenarios are benchmarked against the first-best Pigovian tax on transport externalities. Assessing demand shifts, consumer surplus, and external costs, we find that subsidizing night train prices, the aviation tax, and the 2030 scenario increase welfare, whereas a 6% SAF mandate reduces it.

Keywords: Discrete choice models, mode choice, holiday, carbon offsetting, sustainable aviation fuel, night train.
JEL Codes: D6, R4, Q5

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1 Introduction

The European long-distance travel sector is undergoing significant changes due to growing climate awareness among consumers and targeted policy action aimed at reducing emissions. In this paper, we focus on the demand for long-distance train travel as an alternative to flying or driving. Our analysis is based on a stated-preference survey in Switzerland.

Demand for night train travel has grown significantly in recent years (Austrian Federal Railways, 2024; Swiss Federal Railways, 2024). On the supply side, this has been met with a revival of the European night train network, led by the Austrian train operator ÖBB that has made significant investments in modernizing its fleet to enhance the attractiveness of this mode of transport. This new generation of "nightjet" trains has been gradually rolled out since December 2022 (Austrian Federal Railways, 2024). In Switzerland, governmental support of night train travel is a recurring topic in political debates. This resulted in the inclusion of a subsidy of up to 30 million Swiss francs[1] per year for night trains in the current version of the Swiss CO_2 Act (Article 37a), effective until 2030.[2]

Another policy under consideration in Switzerland is a tax on airline tickets for flights originating or ending in Switzerland, with the aim of shifting some travel to alternative modes. Although not included in the current CO_2 Act, environmental organizations continue to advocate for a flight tax. At the European scale, multiple transnational policies are expected to have an important impact on long-distance travel. The aviation sector has been part of the EU Emissions Trading System (EU ETS) since 2012. However, the auctioning of allowances is only being phased in and will be fully implemented by 2026.[3] The resulting increase in airlines' average costs, combined with projected rises in EU allowance prices, could translate into higher ticket prices.

Additionally, the EU initiative ReFuelEU Aviation established mandatory blending quotas for sustainable aviation fuel (SAF) on flights within or departing from the EU, with quotas starting at 2% in 2025, gradually increasing to 6% by 2030 and to 70% by

[1] In February 2025, one Swiss franc (abbreviated CHF) was equivalent to €1.07 and $1.11.

[2] Federal Act of December 23, 2011 on the Reduction of CO_2 Emissions (CO_2 Act), SR 641.71 and according to amendment AS 2024 376; BBl 2022 2651 in force as per January 1, 2025.

[3] Directive (EU) 2023/958 of the European Parliament and of the Council of 10 May 2023, amending Directive 2003/87/EC.

2050.[4] Switzerland has also adopted the EU's regulation on SAF. Blending kerosene with SAF reduces the amount of emissions "newly" added to the atmosphere. A popular and already more established alternative policy consists of purchasing CO_2 offsets to compensate emissions from flying. Many airlines offer voluntary compensation when purchasing airplane tickets, and some even compensate all flight emissions. In principle, reducing or compensating emissions amount to the same thing, but the effectiveness (or "additionality") of offsets remains controversial. A recent review by Probst et al. (2024) found that, on average, fewer than 16% of issued certificates lead to actual emission reductions, casting doubt on their reliability. CO_2 offsets may also serve as a moral justification for flying, potentially leading to increased flight frequency (Gössling et al., 2007; Bösehans et al., 2020). This "rebound" effect, combined with the uncertainty in effectiveness of offsets, poses a challenge to global climate mitigation efforts. Gaining deeper insights into how travelers perceive carbon offsets is therefore essential.

This study examines expected behavioral changes among consumers in response to a set of specific policies. Our results are based on an online discrete choice experiment with 1,073 participants from Switzerland. The respondents were presented with a one-week holiday scenario offering the train, night train, airplane, and car (electric or combustion) as travel alternatives. We estimate mixed nested logit models to derive price and cross-price elasticities, along with willingness-to-pay (WTP) for carbon offsets, SAF, shorter travel times, and improved travel comfort. We find values of travel time savings (VTTS) around CHF 15-17 per hour for air and train travel, and CHF 13-14 for night trains and cars. We find a high WTP for SAF, but not for carbon offsets. Train and night train demand is elastic with respect to cost and time, whereas car and air travel demand is considerably less so. Education and age are important moderators, and imagining the trip with children increases the baseline preference for car travel while also raising VTTS for car and train.

In a second step, we use our model to compute the change in market shares, consumer surplus, and aggregate welfare in response to five specific policies: (i) a Pigovian transport,

[4] Regulation (EU) 2023/2405 of the European Parliament and of the Council of 18 October 2023 on ensuring a level playing field for sustainable air transport (ReFuelEU Aviation); OJ L, 31.10.2023, ELI: `http://data.europa.eu/eli/reg/2023/2405/oj`.

tax, (ii) a subsidy for night trains, (iii) a flight tax, (iv) the introduction of an SAF quota and (v) an SAF quota combined with an increase in night train comfort. When treating emissions reductions in aviation and trains as additional to the EU ETS, all policies except the SAF quota generate positive welfare effects. If, however, we assume that the reductions in flight and train emissions are completely neutralized by the presence of the EU ETS, the positive net welfare effects of both the night train subsidy and the aviation tax diminish. Our results therefore imply that smart transportation policies can result in a real societal benefit, but in order for this benefit to materialize, it is important to consider other existing policies. In our context, this means that the ETS cap would need to be adjusted in response to these policies. Otherwise, the decrease in emissions associated with a mode shift from air to rail is offset by an increase in emissions elsewhere.

The paper proceeds as follows. In the next section, we provide a brief review of the relevant literature. Section 3 describes our study design and the data. Sections 4 and 5 present our econometric model and the results, respectively, and section 6 contains our policy simulations that are based on these estimates. Section 7 concludes.

2 Literature review

A number of previous papers focus on long-distance mode choice by means of stated preference surveys and discrete choice models. Typically, these studies focus on key attributes such as travel time, travel cost, and the ease of connections (Arbués et al., 2016; Hess et al., 2008; de Lapparent et al., 2009; Andersson et al., 2022; Bursa, 2024; Thrane, 2015; Limtanakool et al., 2006). Some studies include additional attributes such as comfort, access/egress, and trip frequency for Europe (Schatzmann and Axhausen, 2021; Rich and Mabit, 2012; Van Acker et al., 2020; Rohr et al., 2013) or the U.S. (Moeckel et al., 2015).

The previous literature has primarily examined car, bus, air, and conventional train travel. Night trains have only recently started to receive attention. Kantelaar et al. (2022) analyze the willingness to use night trains as an alternative to airplane travel in the Netherlands. Their results indicate that comfort plays a significant role in night train travel decisions. Buh and Peer (2024) confirm this finding and add that perceived lack of security is a further barrier, especially for female travelers. Using a Theory of Planned Behavior framework, they find that familiarity with night train travel and environmental concerns increase the intention to use night trains. Morfeldt et al. (2023) analyze scenarios of carbon footprint reductions by shifting holiday travel of Swedish tourists from airplanes to night trains, while Avogadro et al. (2021) do the same for entire Europe but focusing on the shift to high-speed train travel. Gerosa and Cellina (2024) profile actual night train users in Switzerland through a mixed-method study, identifying distinct traveler segments such as “greens”, who consistently choose rail for environmental reasons, “pragmatists”, whose choices depend on price and convenience, and “dissonants”, who reconcile sustainable daily travel with frequent flying. Their analysis shows that ticket cost is the key factor differentiating mode choices between segments. Focusing on the supply side, Rickfelder and Schönberger (2024) develop a graph-theoretical approach to estimate demand potentials for international passenger rail with a specific application to European night trains.

Limited research exists on the relative roles of carbon offsetting and SAF in mode choice. Schwirplies et al. (2019) analyze individuals’ willingness to offset CO_2 emissions from leisure and business travel by bus and airplane using discrete choice experiments with varying framings. They find a substantially higher willingness to offset emissions from bus trips compared to air travel (€44 versus €10 per ton of CO_2e reduced). Carroll et al. (2022) estimate that households are, on average, willing to pay €77 per ton of CO_2 reduced. Berger et al. (2022) analyze real booking data from a Swiss airline, and find a significantly lower WTP of approximately €1 for carbon offsetting, with only 4.5% of all bookings opting to offset their emissions. Our findings align with the mixed evidence in the literature. While we do not find a significant WTP for carbon offsetting, the estimated WTP for a 100% emission reduction via SAF amounts to CHF 94 per ton of CO_2e.

Several studies have explored the effects of different transport policy interventions, such as aviation taxes and investments in night trains, on travel behavior and mode shares. A survey by the Europe on Rail (2021) network evaluates the potential for night trains and estimates that 32% of all EU aviation passengers would switch to night trains if night train alternatives were offered for destinations in between 500 and 3,000 kilometers. Curtale et al. (2023) conclude from their stated preference experiment that in response to innovations such as reduced travel time and more comfortable trains, the share of Swedish plane users willing to switch to night trains could reach 20–30% for Central Europe, and 6–10% for Southern Europe. Morfeldt et al. (2023) suggest that a mode shift from airplane to night trains in Sweden could be driven by progressive policies that reduce transfers and align train prices with airfares, potentially increasing market share from below 10% to 30%, and reducing emissions from long-distance travel by 9%. Our study also finds that night train demand responds to changes in comfort, time, and air travel costs, and amounts to a share of 20.7% of our choice situations.

Bernardo et al. (2024) analyze the impact of aviation taxes on low-cost airlines and CO_2 emissions with a dataset on airplane travel within Europe. Using a staggered difference-in-differences approach, they find that the taxes reduce the number of flights per airline-route by 12%, resulting in a 14% decrease in carbon emissions. Using the same approach, Falk and Hagsten (2019) find that a flight departure tax implemented in Germany and Austria in 2011 led to a 9% decrease in the number of passengers in the year of introduction and a 5% reduction in the following year. Our study estimates that the proposed aviation tax reduces the market share of air travel by 6 percentage points (an 18.7% reduction from the baseline share of 32.1%).

There exist numerous theoretical contributions comparing welfare outcomes across different transport policies, but empirical evidence remains scarce. Zheng et al. (2024) compare the environmental and welfare impacts of subsidy and quota policies for promoting SAF usage. They find that the subsidy policy leads to higher social welfare, consumer surplus, and industry profits, particularly when traditional aviation fuel (TAF) prices are low and emission regulations under the subsidy policy are stringent. Jiang and Yang (2021) compare the welfare effects of a carbon tax versus a SAF quota in a theoretical model. The SAF quota can outperform the carbon tax in emission control and welfare when SAF prices fall or TAF prices are low, but the carbon tax may lead to higher welfare without uncertainty in the TAF price. Keshavarzzadeh et al. (2022) develop a meta-heuristic framework to optimize quota and tax regimes for Switzerland's aviation industry. Their findings suggest that optimized SAF quotas, combined with a well-shaped tax regime and investment in SAFs, are more effective than high carbon taxes alone in maximizing social welfare and reducing emissions. Proost (2024) examines the welfare impacts of carbon taxes, emission permits, SAF mandates, and fuel efficiency standards in the aviation sector. The theoretical model shows that the welfare effects of SAF blending mandates are the lowest compared to other policy instruments.

Our work analyzes European holiday travel, with a focus on the demand for modern night train trips in the context of more sustainable air travel. It contributes to the evaluation of current and planned policies in several ways, making this paper particularly relevant for policymakers. Our discrete choice experiment is unique in enabling a comprehensive estimation of preferences for leisure travel, explicitly incorporating the night train alongside other main modes. By integrating the new, more comfortable night train cabins, we can analyze current travel mode preferences with a specific focus on comfort. Second, we incorporate two crucial attributes of modern air travel: SAF and carbon offsetting. This enables us to offer new insights into the role of these attributes in travel mode choice, an area that has been largely unexplored. By including SAF and carbon offsetting within the same choice experiment, we can directly compare their attractiveness to consumers, and offer a new perspective on the effectiveness and credibility of carbon offsetting schemes. Third, our welfare estimates offer insights into the societal desirability of planned transport policies. They explicitly account for the intricate role of the EU ETS in regulating aviation emissions and benchmark the results against the first-best solution of a Pigovian tax on external costs.

3 Study design and data

To analyze travel decisions, we ask participants to imagine a one-week holiday trip to a European destination of their own choice (see Appendix A). The destination should be easily accessible and approximately 700 kilometers away from home. By keeping travel distances constant across alternatives, we focus on mode choice rather than destination choice. Based on all attributes shown, participants have to choose between four different means of transport: Car (electric or combustion), train, night train, and airplane. The car option is only displayed to participants who reported having access to a car. Since bus and coach trips represent a relatively small share of the transport market in Switzerland (European Commission, 2021), we ignore these modes.

Figure 1 shows an example of a choice situation displayed to the respondents. We choose the attributes according to prior findings in the literature (travel time, cost, and comfort), and with a focus on our research questions (sustainable fuel and carbon offsetting). We limit ourselves to these five attributes to not overwhelm choice takers.

Figure 1: Example choice situation shown to participants

Travel cost	92 CHF	92 CHF	92 CHF	68 CHF
Travel time Door-to-door	7:40 h	6:35 h	7:40 h	4:30 h
Comfort				Economy
Sustainable fuel				☑
CO2 offsets				☒
Emissions in kg CO2e	132 kg	29 kg	44 kg	212 kg ÷ 2 = 106 kg

The participants receive an introductory explanation of all attributes (see Appendix A). They are informed that, even though distance is fixed, travel times vary due to differences in connections, traffic congestion, and other factors affecting duration. Table 1 presents the varying attribute levels across all modes. Details on the calculation of travel costs and times are provided in Appendix B.

We include two comfort categories for day trains (first and second class), and three categories for night trains (6-bed couchette, 4-bed couchette, and 2-bed sleeper cabin). The comfort attribute excludes business-class flights, as their share among leisure travelers is negligible, whereas first-class train travel is common in Switzerland (Swiss Federal Railways, 2014). The comfort attributes are presented in the form of images, as shown in Figure 2.

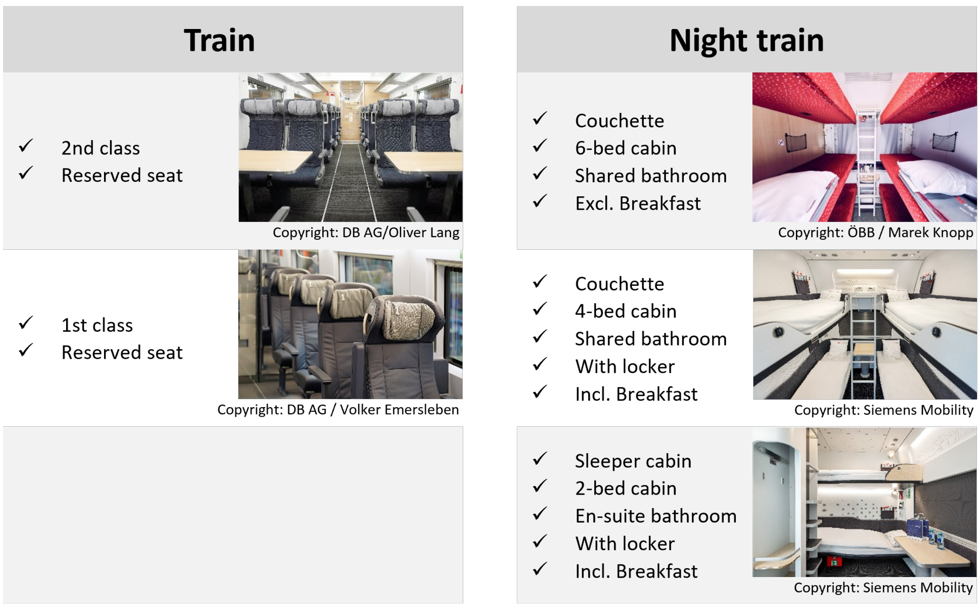
The binary attribute *sustainable fuel*, indicating reduced emissions, is explained to participants as follows: "Sustainable fuel is a mixture of conventional kerosene and fuel

Table 1: Attribute levels

	Unit	Car	E-car	Train	Night train	Airplane
Travel cost	CHF	53	53	53	53	68
		68	68	92	92	92
		92	92	115	115	115
				142	142	142
Travel time	hh:mm	7:40	7:40	6:35	7:40	3:35
		8:25	8:25	7:40	8:25	4:30
		9:30	9:30	8:25	9:30	
Comfort	Category			2nd class	6-bed couchette	
				1st class	4-bed couchette	
					2-bed sleeper cabin	
Sustainable fuel	Binary					No
						Yes
Carbon offsets	Binary					No
						Yes
Emissions	kg	132	74	29	44	212
						106

Notes: The table outlines the attribute levels for all modes varied in the study. While travel distance is constant as defined in the scenarios, travel times vary. Depending on the respondent's access, either a car, an e-car, or no car option is displayed. For flights with SAF, the emissions indicated are reduced by 50%.

Figure 2: Comfort levels



Notes: This figure illustrates the comfort levels as explained in the introductory text. In the subsequent choice situations, only the respective image is presented.

obtained from renewable sources. For this, CO_2 is taken from the atmosphere or recycled from plant waste and converted into synthetic fuel with the help of a chemical process. By using this blended kerosene, only half as many new greenhouse gases are emitted into the atmosphere. The saving of 50% of emissions is shown as follows: 212/2 = 106 kg." This definition abstracts from the various different types of SAF considered by the EU legislation,[5] but it conveys the key points on SAF while limiting the cognitive burden. Finally, we include an indicator for whether emissions are compensated using carbon offsets. Participants are informed that carbon offsetting reduces emissions "by investments in renewable energies, energy efficiency measures as well as forest protection, reforestation or re-naturalization of moorland". CO_2 emissions vary only through the SAF attribute, so preferences for emission reductions are identified within the flight mode. For other modes, environmental concerns are absorbed in the general preference for each mode (i.e., the alternative-specific constant). Emission levels are displayed for all modes to support informed choice.

All attributes are orthogonalized using nGene subject to constraints.[6] For example, we allow some attributes to correlate to a limited extent, as excessively diverging attribute levels could be perceived as unrealistic. These attributes include comfort and costs in train rides, as well as cost differences between train, night train, and airplane alternatives. The resulting correlation matrix of our choice attributes is presented in Appendix C. We implement a block design with six choice situations per respondent to balance cognitive burden and statistical efficiency. To increase variation and improve estimation precision, the design is divided into six different blocks, with each participant randomly assigned to one of them (see Appendix C). The order of the six choice situations within each block is also randomized. Participants without access to a car were assigned to the same block design, but the car option was simply not displayed to them.

To enhance the realism and personal relevance of the choice scenarios, participants are asked how they imagine taking the trip: alone, with children, with family members but without children (e.g., parents or relatives), with a partner, or with friends (see Figure A.2 in Appendix A). This question captures the situational context of the trip and allows us to identify preference heterogeneity between different travel constellations (see Appendix D

[5]Regulation (EU) 2023/2405 of the European Parliament and of the Council of 18 October 2023 on ensuring a level playing field for sustainable air transport (ReFuelEU Aviation) (OJ L, 2023/2405, 31.10.2023, ELI: `http://data.europa.eu/eli/reg/2023/2405/oj`).

[6]`https://choice-metrics.com/`

for the distributions across travel scenarios). We refer to this as the situational variable, although it is constant across all choice situations of the same individual. Importantly, the block design is independent of the answer to the situational question; that is, the assigned choice situations remain the same regardless of the trip context selected. Lastly, participants answer a set of socio-demographic questions, which may also help identify preference heterogeneity.

Table 2: Characteristics of participants

Category	Level	Unit	Unweighted	Weighted	Microcensus
Access to car	Yes	%	86.3	88.8	88.8
	No	%	13.7	11.2	11.2
Access to e-car	Yes	%	3.9	1.5	1.5
	No	%	96.1	98.5	98.5
Age	<36 years	%	25.9	27.7	27.7
	36-60 years	%	51.9	47.6	47.6
	>60 years	%	22.2	24.7	24.7
Gender	Female	%	50.3	50.3	50.5
	Male	%	49.7	49.7	49.5
Education	Mandatory	%	3.4	10.4	12.4
	Secondary	%	43.2	48.3	47.2
	Tertiary	%	53.3	41.4	40.4
Monthly household income	<10,000 CHF	%	60.8	56.1	56.6
	≥10,000 CHF	%	29.2	19.8	19.7
	Unknown	%	10.1	24.1	23.7
Language	German	%	61.8	69.1	68.8
	French	%	21.4	25.2	25.3
	Italian	%	16.8	5.7	5.9
Urbanity level	Urban	%	65.0	64.3	64.3
	Agglomeration	%	22.0	20.3	20.4
	Rural	%	13.0	15.3	15.3

Notes: Descriptive statistics shown for this study's sample, before and after weighting, as well as the Swiss Mobility and Transport Microcensus 2021 sample (Swiss Federal Office of Statistics and Swiss Federal Office of Spatial Development, 2023).

We distributed our survey as part of a YouGov summer holiday survey in May 2023.[7] 16% of the initially contacted respondents (N = 1,620) do not plan any summer holidays and are thus excluded from the survey, and 8% are excluded due to providing incomplete responses. We additionally exclude the participants (9% of the total) who completed the entire survey in less than 5 minutes or spent less than 20 seconds viewing the explanatory

[7] `www.yougov.ch`, formerly known as the LINK research institute.

text (shown in Appendix A). This data cleaning process retains 1,073 survey participants with valid answers. Overall, we achieve a total of 6,438 choice observations.

Table 2 presents the summary statistics for key socio-demographic variables of our sample and compares them with data from the Mobility and Transport Microcensus (MTMC), which is a representative travel diary survey conducted by the Swiss Federal Statistical Office and the Federal Office for Spatial Development (2023). The comparison shows that the sample is generally better educated and has a higher income than the general population. The discrepancy in access to electric vehicles is likely over-stated by the fact that the Microcensus only reports e-car ownership, whereas our study includes general access to e-cars. Nevertheless, to address concerns about non-representativeness, we construct sample weights to match population averages in Switzerland.[8]

4 Methodology

We estimate different types of discrete choice models, following the foundational framework for discrete choice experiments (Train, 2002; Hensher et al., 2015).[9] Based on the model coefficients, we then predict how changes in attributes affect mode choice and quantify the resulting impacts on consumer surplus and overall welfare.

Our analysis is based on a random utility model (RUM) with linear-additive utility functions. We estimate multinomial logit (MNL), nested logit (NL), mixed multinomial logit (Mixed MNL), and mixed nested logit (Mixed NL) models, with the latter two capturing taste heterogeneity through the deterministic component of utility rather than solely via the error term (Fiebig et al., 2010). The nested structure accounts for the relatedness of train and night train alternatives, reflecting a sequential decision process: first whether to travel by train, and if so, which time of day.

[8]Weights are generated using a raking algorithm (Pasek, 2018), aligning our sample with all variables listed in Table 2 and imposing a maximum weight of 3.

[9]All models are estimated using maximum likelihood based on the *apollo* package of Hess and Palma (2019).

We denote the utility of person n choosing alternative i in choice situation t as

$$U_{i,n,t} = \alpha_i + \mathbf{x}'_{i,n,t}(\beta_i + \eta_{i,n}) + \nu_{i,n} + \epsilon_{i,n,t} \tag{1}$$

where the error component $\epsilon_{i,n,t}$ is assumed to follow an IID extreme value type I distribution. We allow the preferences for the attributes, and for the unobserved determinants of the alternatives themselves, to vary across individuals. The coefficient α_i captures the average utility of each alternative (relative to the reference category), while the random intercepts, $\nu_{i,n}$, account for unobserved individual-specific heterogeneity in these baseline preferences. Similarly, β_i reflects the average preference vector associated with alternative i, whereas $\eta_{i,n}$ captures the variation across individuals. We assume a negative log-normal distribution of $\beta_{cost,n}$ for travel costs to ensure negative coefficients, i.e. $\beta_{cost,n} = -\exp(b + \sigma d_N), \quad d_N \sim N(0,1)$. For all other attributes in the vector $\mathbf{x}'_{i,n,t}$, we assume normal distributions of $\beta_{i,n} \equiv \beta_i + \eta_{i,n}$.

To directly interpret the results in monetary terms, we estimate all models in WTP-space rather than preference-space. This involves re-parameterizing the utility coefficients by dividing them by the individual-specific cost coefficient, $\beta_{cost,n}$. To implement this transformation, the coefficients of all non-cost attributes are multiplied by $\beta_{cost,n}$. This transformation allows us to estimate ratios of coefficients, which can then be directly interpreted in monetary units (e.g., how much someone is willing to pay to avoid travel time). The choice probabilities in all mixed models are estimated using 5,000 Modified Latin Hypercube Sampling (MLHS) draws (Hess et al., 2006).

To estimate the behavioral changes in the scenarios, we adjust the corresponding attributes in $\mathbf{x}'_{i,n,t}$ and forecast the individual changes in mode choice. We also compute the expected change in utility that results from this adjustment; following McFadden (1977) and Small and Rosen (1981), we can express the expected consumer surplus as

$$E\left[CS_{n,t}\right] = E\left[\frac{1}{|\beta_{cost,n}|} \max_{i \in I} U_{i,n,t}\right], \tag{2}$$

where $U_{i,n,t}$ represents the utility for individual n choosing alternative i in choice situation t. Although the utility $U_{i,n,t}$ is unobservable, the expected consumer surplus can still be derived from the observed utility $V_{i,n,t} \equiv x_{i,n,t}(\beta_i + \eta_{i,n})$ under the assumption that the error terms follow an i.i.d. Extreme Value Type I distribution, as in Equation 1. By dividing the expected utility by the marginal utility of income, $\beta_{cost,n}$, we obtain a money-metric measure of consumer surplus. This allows us to reformulate Equation 2 as:

$$E\left[CS_{n,t}\right] = \frac{1}{|\beta_{cost,n}|} \cdot \ln\left(\sum_{i=1}^{I} \exp(V_{i,n,t})\right) + C_{n,t}, \tag{3}$$

commonly referred to as the *logsum* for individual n and choice situation t. Following Train (2002) and originally based on Ben-Akiva (1973), we further account for the nesting structure by first computing the inclusive value of the train nest and then the upper-level logsum. In Equation 3, this corresponds to replacing the term $\sum_{i=1}^{I} \exp(V_{i,n,t})$ with

$$\exp(V_{\text{car},n,t}) + \exp(V_{\text{airplane},n,t}) + \left[\exp\left(\frac{V_{\text{train},n,t}}{\lambda}\right) + \exp\left(\frac{V_{\text{night train},n,t}}{\lambda}\right)\right]^{\lambda}$$

where λ is the dissimilarity parameter (also called the inclusive value parameter), measuring the degree of independence in unobserved utility within the train nest. $\lambda = 1$ implies no correlation of unobserved utility within the nest (reducing to the MNL), while values closer to zero indicate stronger correlation, meaning that unobserved factors affecting one train option are more likely to also affect the other. Using our experimental data and model predictions, we compute the difference in monetized utility before and after changes in attribute values based on the conditional (posterior) parameter distributions, where the constant (and econometrically unidentified) parameter $C_{n,t}$ cancels out.

5 Estimation results

We develop our models sequentially. We begin with a simple nested logit (NL) model, which is subsequently extended by interactions with situational and socio-demographic variables. Guided by likelihood ratio tests, we only retain interactions which explain mode choice behavior with enough statistical significance. Table 3 reports five models. The first column (NL) presents the baseline nested logit including all alternative-specific attributes. The second model (Mixed NL) adds random components (mixing), while the third model (NL Interac.) adds situational and socio-demographic interactions. The final model extends this by adding random components. Weights are not used in estimation but to compute representative elasticities and market shares.

In all models, the "airplane" mode serves as the reference category. We include separate dummies for each comfort level, using second class for regular trains and 6-bed couchette for night trains as reference categories. Since the models are estimated in WTP-space, all coefficients, except the constants (ASC), can be directly interpreted in monetary values (in CHF). For travel time, the coefficients represent the average estimated VTTS for a one-hour reduction in travel time. In Appendix E we show the posterior distributions of model 2.

Across all estimated models, travel cost, travel time, sleeper cabin availability, and SAF emerge as the primary attributes influencing the mode choice for holiday travel. The strong influence of travel time and cost aligns with findings from previous studies (Schatzmann and Axhausen, 2021; de Lapparent et al., 2009). In the following, we interpret the coefficients of model 2, as it allows for full random taste variation and enables direct interpretation of average VTTS and WTP across all respondents. Models 3 and 4 explore preference heterogeneity and are thus less suitable for the interpretation of average effects.

We estimate the highest VTTS for air travel at CHF 17.3 per hour, followed by trains (CHF 15.4/h), cars (CHF 13.8/h), and night trains (CHF 12.9/h), all statistically significant at $p < 0.001$. Our VTTS estimates are slightly lower but broadly consistent with findings in the literature (see, e.g., Tao and Zhu, 2020; de Lapparent et al., 2009; Hess et al., 2008; Schatzmann and Axhausen, 2021; Monchambert, 2020). Weighting the individual-specific preference parameters using the weights described in section 3 leaves the average VTTS estimates unchanged up to one decimal place. The WTP estimates for first-class travel and 4-bed couchettes are not significant, suggesting limited gains compared to their reference categories.

Table 3: Regression estimates

	Coefficient	(1) NL	(2) Mixed NL	(3) NL Interac.	(4) Mixed NL Interac.
Travel Cost	Travel Cost	-0.009***	-3.821***	-0.010***	-3.655***
		(0.001)	(0.103)	(0.001)	(0.072)
	$\sigma_{\text{Travel Cost}}$		1.039***		0.929***
			(0.105)		(0.105)
Travel Time	TT-Train	22.151***	15.429***	20.578***	13.574***
		(2.873)	(1.334)	(3.643)	(2.429)
	$\sigma_{\text{TT-Train}}$		0.910***		1.550***
			(0.443)		(0.485)
	TT-Night Train	10.185***	12.870***	12.679**	11.340***
		(2.614)	(1.281)	(4.172)	(2.273)
	$\sigma_{\text{TT-Night Train}}$		1.880***		1.139
			(0.318)		(0.285)
	TT-Car	16.657***	13.775***	18.391*	13.153***
		(4)	(1.429)	(7.244)	(2.593)
	$\sigma_{\text{TT-Car}}$		1.604**		5.939***
			(0.219)		(0.734)
	TT-Airplane	15.868**	17.297***	6.836	13.117***
		(5.832)	(2.392)	(6.283)	(3.597)
	$\sigma_{\text{TT-Airplane}}$		4.476***		2.444*
			(0.42)		(1.713)
Comfort	First Class	-5.547	-5.156	6.182	0.027
		(3.873)	(3.731)	(6.03)	(4.198)
	$\sigma_{\text{First Class}}$		27.251***		18.597**
			(4.147)		(6.046)
	Couchette (4-Bed)	-8.059	-2.053	-9.199	-2.966
		(5.977)	(3.911)	(6.005)	(3.669)
	$\sigma_{\text{Couchette (4-Bed)}}$		12.838***		11.595***
			(1.938)		(3.126)
	Sleeper Cabin	-16.255**	-6.352	-17.117**	-6.649
		(5.479)	(5.273)	(5.599)	(4.746)
	$\sigma_{\text{Sleeper Cabin}}$		38.740***		37.723***
			(11.533)		(7.646)
Emissions	Carb. Offsets	-9.343	-4.000	-8.357	-3.450
		(8.772)	(4.283)	(8.344)	(4.583)
	$\sigma_{\text{Carb. Offsets}}$		24.647***		27.737***
			(2.588)		(5.077)
	SAF	-16.003*	-10.003*	-14.652.	-10.226*
		(7.983)	(4.285)	(7.534)	(4.458)
	σ_{SAF}		19.587***		18.451.
			(2.657)		(10.112)
	Carb. Offsets x SAF	3.787	-1.959	2.242	-2.728
		(13.330)	(6.020)	(12.631)	(6.662)
	$\sigma_{\text{Carb. Offsets x SAF}}$		10.353**		19.039*
			(3.365)		(7.303)
Nesting	$\lambda_{\text{Train-modes}}$	0.565***	0.566***	0.597***	0.628***
		(0.054)	(0.088)	(0.065)	(0.081)
Model Fit	LL(final)	-8297	-5201.7	-8070	-5140.7
	McFadden R^2	0.026	0.387	0.05	0.392
	AIC	16624	10463.4	16212	10383.4
	BIC	16725.6	10666.5	16455.7	10728.7
	Avg. Likelihood	0.282	0.485	0.296	0.49

Notes: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $.\,p < 0.1$. The table reports results from nested logit (NL) regressions estimated in WTP-space, so coefficients directly represent WTP in CHF (or VTTS in CHF/h). Models 1 and 3 do not include random coefficients, whereas models 3 and 4 include interactions. *Continued.*

	Coefficient	(1) NL	(2) Mixed NL	(3) NL Interac.	(4) Mixed NL Interac.
Constants	ASC Train	0.884**	1.736***	1.099***	2.133***
		(0.279)	(0.265)	(0.297)	(0.392)
	$\sigma_{\text{ASC Train}}$		1.559***		1.166
			(0.301)		(0.254)
	ASC Night Train	-0.013	1.221***	0.526	1.509***
		(0.266)	(0.279)	(0.36)	(0.417)
	$\sigma_{\text{ASC Night Train}}$		1.538***		1.922***
			(0.35)		(0.245)
	ASC Car	0.209	-0.772.	0.729	0.191
		(0.349)	(0.411)	(0.608)	(0.612)
	$\sigma_{\text{ASC Car}}$		5.657***		4.327***
			(0.378)		(0.428)
	$\sigma_{\text{ASC Airplane}}$		4.882***		4.681***
			(0.302)		(0.29)
Situational	ASC Car x Children			1.503.	3.21***
				(0.782)	(0.709)
	ASC Car x Other			-1.755	-10.564***
				(1.16)	(3.128)
	TT-Train x Children			6.81***	4.819***
				(1.566)	(1.268)
	TT-Train x Other			-7.305***	-3.37*
				(1.765)	(1.48)
	TT-Car x Children			14.444	8.474***
				(9.745)	(2.019)
	TT-Car x Other			-19.124	-25.206***
				(13.487)	(7.392)
Socioecon.	ASC Train x French			-0.29*	-0.658
				(0.137)	(0.409)
	ASC Train x Italian			-0.055	-0.187
				(0.153)	(0.415)
	ASC Night Train x French			-0.368**	-0.968*
				(0.141)	(0.455)
	ASC Night Train x Italian			-0.567***	-1.364**
				(0.165)	(0.462)
	ASC Night Train x >49 Years			-0.698	-0.077
				(0.427)	(0.572)
	ASC Car x >49 Years			-0.834	-3.109***
				(0.648)	(0.675)
	ASC Car x Urban			-0.35**	-1.01*
				(0.133)	(0.447)
	TT-Train x Tert. Educ.			8.434*	4.656
				(3.298)	(2.94)
	TT-Train x >49 Years			-4.402*	0.119
				(1.732)	(1.655)
	TT-Night Train x Tert. Educ.			6.592*	3.223
				(2.967)	(2.623)
	TT-Night Train x >49 Years			-11.984*	-0.453
				(5.197)	(1.854)
	TT-Car x Tert. Educ.			10.911***	6.045*
				(3.226)	(2.701)
	TT-Car x >49 Years			-17.519*	-15.461***
				(7.951)	(2.023)
	TT-Airplane x Tert. Educ.			14.555*	7.834
				(6.07)	(4.805)
	First Class x >49 Years			-23.719**	-18.157**
				(7.892)	(6.709)

Continuation: Because coefficients are scaled by the (negative) cost coefficient, a negative sign indicates that an attribute is associated with a positive WTP. For variable definitions, see section 3. Standard errors in parentheses (tested against 1 for σ- and λ coefficients). The reference category is airplane. Coefficients for the alternative-specific constants (ASC) and their interactions are not estimated in WTP-space and can only be interpreted relative to each other. The situational variable captures the imagined trip type: (i) with other adults (reference category), (ii) with children, or (iii) other (alone or "Other" responses). Average likelihoods are reported relative to that of an MNL model with only ASCs (0.270).

For flying, the use of SAF increases the utility, with an average WTP of CHF 10. This indicates that travelers are more likely to choose air travel when SAF is available, suggesting a rebound effect. In contrast, the lack of statistical significance for the coefficient on carbon offsets shows that they have little influence on mode choice and thus likely do not induce a considerable rebound effect. The corresponding weighted WTP estimates for SAF and carbon offsets are CHF 9.9 and CHF 4.4, respectively.

With SAF described as reducing flight emissions by 50%, the amount of emissions that can be offset with certificates depends on whether the SAF attribute is active. This is why we include an interaction which captures the hypothesis that each of the two attributes is valued less when the other is already present, which would show in a negative WTP. Although the point estimates in models 1 and 3 are positive, they are identified very imprecisely and are far from reaching statistical significance. Across all mixed models (including the robustness checks in Appendix F), the interaction coefficient centers around zero. Additionally, excluding the interaction term does not alter the remaining coefficients and maintains the same goodness of fit. This consistent null finding suggests that respondents did not perceive this design detail, but reacted mainly to the presence or absence of the attributes *carbon offsets* and *SAF*. We nevertheless retain the interaction term in our main specification, given its theoretical relevance.

The high WTP for SAF suggests that Swiss travelers are willing to shoulder a meaningful share of the costs of their carbon emissions. For a 100% reduction using SAF, the implied value of CHF 94 per ton of CO_2e is below the newly updated social cost of carbon (CHF 430; Ecoplan-INFRAS, 2024), but nonetheless reflects a substantial willingness to contribute to climate mitigation through cleaner aviation fuels.[10]

We group the situational contexts into three categories: (i) trips with other adults (reference category), (ii) trips with children, and (iii) other (traveling alone or "Other" responses; see Figure A.2). This aggregation ensures sufficient sample size per category while maintaining a meaningful distinction between family-oriented and individual travel contexts. Models 3 and 4 show that respondents imagining a trip with children prefer the car and exhibit a higher VTTS for train and car, with no significant differences across

[10]Based on the WTP estimate from model 2 in Table 3: CHF $10.003 \cdot 2 \cdot \frac{1000 \text{ kg } CO_2e}{212 \text{ kg } CO_2e}$ = CHF 94.37/t.

trains, night trains, and airplanes. Socio-demographic interactions show that preferences vary mainly by age and education, with older individuals having a higher WTP for first class. We find weaker preferences for night trains among French- and Italian-speaking respondents. Including a dummy indicating whether a respondent lives within 50 km of a night-train station does not change this result, which suggests that this does not capture lower accessibility or service provision.[11] People with a tertiary education do not show different preferences for SAF or carbon offsetting. None of the models showed any significant differences based on gender. Table F.1 in Appendix F tests the income elasticity of cost sensitivity, which is not significant.

Table 4: Elasticities and marginal probability effects

	Train [%]	Night Train [%]	Car [%]	Airplane [%]
Cost-Train (+ 1%)	-1.00	0.58	0.18	0.21
Time-Train (+ 1%)	-1.26	0.76	0.25	0.28
Cost-Night Train (+ 1%)	0.47	-1.21	0.17	0.20
Time-Night Train (+ 1%)	0.54	-1.30	0.21	0.25
Cost-Car (+ 1%)	0.14	0.15	-0.48	0.13
Time-Car (+ 1%)	0.15	0.17	-0.44	0.10
Cost-Airplane (+ 1%)	0.31	0.36	0.26	-0.70
Time-Airplane (+ 1%)	0.22	0.25	0.18	-0.46
Carbon Offsets (dummy)	-1.07	-1.22	-1.53	3.09
SAF (dummy)	-3.12	-3.62	-3.05	7.20
First Class (dummy)	10.54	-5.30	-2.40	-2.53
4-bed Couchette (dummy)	-1.54	4.55	-0.75	-0.88
Sleeper Cabin (dummy)	-3.74	17.06	-3.02	-3.17

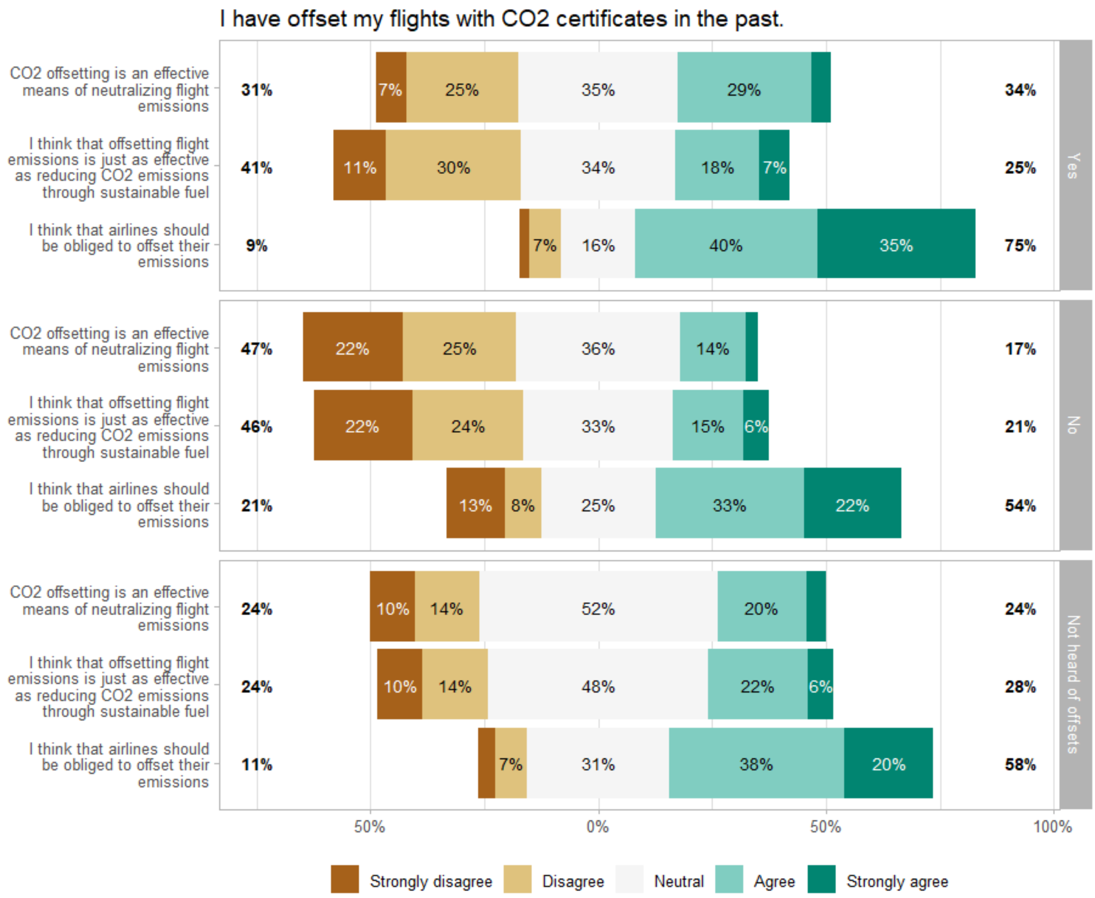
Notes: The elasticities describe the change in the choice probability per mode in percent in response to an increase by 1% in the attributes (on the left). For dummies, they show the change in the choice probabilities for a switch from 0 to 1. The interaction of carbon offsets and SAF is set to zero to calculate independent elasticities for the two attributes. The results are based on model 4 in Table 3 and include the sample weights presented in Table 2.

Table 4 displays the average responsiveness of choice probabilities to a change in the respective attribute while keeping all other attributes fixed. These own- and cross-price elasticities describe the probability of changing the corresponding mode when the attribute on the left increases by 1%, or when dummy variables switch from 0 to 1. Ceteris paribus, a sleeper cabin increases the marginal choice probability for night trains by 17.1%. Carbon

[11] At the time of writing, the four stations offering night-train services in Switzerland are Basel, Zürich, Sargans, and Buchs SG

offsetting increases the probability of flying by 3.1%, whereas SAF increases it by 7.2%. Demand for train and night train travel is (unit) elastic with respect to cost and time, while travel decisions more generally appear relatively inelastic. These overall low elasticities are consistent with previous research on holiday travel mode choice (Yang et al., 2016; Bursa et al., 2022; Bursa, 2024) and mode choice in general (Wardman et al., 2018).

Figure 3: Survey questions on carbon offsetting and SAF



Notes: This figure illustrates the responses to three Likert-scale questions for individuals who have offset their airplane emissions at least once before (N = 288, top panel), those who have not done so (N = 571, middle panel), and for individuals who have not heard of carbon offsets before the survey (N = 214, bottom panel).

Carbon offsets versus SAF To better understand how travelers perceive carbon offsets and SAF, participants were asked three Likert-scale questions after the choice experiment to assess their opinions on the difference. The responses, summarized in Figure 3, are categorized by individuals who have offset their emissions at least once, those who have not, and those who have never heard of offsets before. Excluding the latter, 44% of respondents do not consider carbon offsets an effective means of neutralizing emissions, while 42% believe SAF to be more effective. Respondents who previously had offset their emissions at least once tend to disagree less with the first statement, but agree that SAF is more effective in achieving actual emission reductions. These individuals also show strong support for mandatory carbon offsetting (75%). As expected, those unfamiliar with carbon offsets tend to have less defined opinions.

6 Policy simulation and welfare impacts

In this section we concretize the transport policies already mentioned in the introduction and present their effects in terms of market shares and welfare. All calculations use the sample weights from Table 2.

6.1 Definition of policy scenarios

We focus on policies that are already implemented or currently being debated in Switzerland. In order to have a benchmark, and to compare them to the optimal policy, we also include a Pigovian tax scenario.

Pigovian tax: We consider this scenario as the first-best approach to fully internalizing externalities, even though such a tax system is not part of current political debates. Furthermore, the external costs that underpin the Pigovian taxes are relevant also for the calculation of the net benefits in the other scenarios.

To compute the Pigovian tax, we focus on the most relevant types of transport externalities. Alongside climate-related externalities (measured by CO_2e emissions), we account for environmental, health and accident-related externalities, as well as time losses due to road congestion. Table 5 shows the person-kilometer values of external costs, by mode of transport and type of externality (for more details, refer to Appendix B). We rely on values computed by Ecoplan-INFRAS (2024) for the Swiss Federal Office of Spatial Development. For night trains, we adjust the external cost factor to 1.09 relative to regular trains. This reflects the lower passenger capacity of night trains (approximately 1.5 times less) while accounting for a higher occupancy rate of 76% during summer, comparable to air travel, instead of the 55% reported for long-distance trains (Sacchi and Bauer, 2023). We abstract from other external costs such as exceeding capacity constraints in public transport and in airports, which may lead to crowding and delays.

Table 5: Marginal external costs by mode (in cents per person-km)

Global view		**Train**	**Night train**	**Car**	**E-car**	**Airplane**
Climate		1.4	1.5	6.4	4.5	12.7
Environment	Nature and landscape	0.7	0.8	0.7	0.7	0.0
	Ground pollution	0.2	0.2	0.1	0.1	-
	Up- and downstream processes	0.3	0.3	3.0	3.6	4.2
Health	Local pollutants	4.2	4.6	2.9	2.7	0.8
	Noise	1.4	1.6	0.8	0.8	0.8
Accidents		0.2	0.2	2.5	2.5	0.2
Congestion		-	-	0.2	0.2	-
Total		**8.4**	**9.1**	**16.5**	**15.1**	**18.7**

Notes: Values based on Ecoplan-INFRAS (2024) and own calculations (see main text).

Night train subsidy: The night train scenario incorporates the recent inclusion of a subsidy for night trains of up to CHF 30 million per year until 2030 in the current version of the Swiss CO_2 Act (Article 37a).[12] We implement this scenario by assuming that 40% of this subsidy is used to reduce tickets prices, whereas the remaining 60% will fund infrastructure investments. Since our model does not capture such investments, we focus on the price rebate only. Based on a subsidy of CHF 30 million and 600,000 night train bookings in 2023 (as stated in the business report of Swiss Federal Railways, 2024), this corresponds to a ticket price reduction of CHF 20. Given the arbitrary nature of the 60/40 allocation, this scenario should primarily be interpreted as an illustration of the potential effects of lower night train fares, rather than as a direct estimate of the welfare impacts of the actual policy.

Aviation tax: This levy of CHF 30 on short- and medium-haul airplane tickets[13] was part of the initial version of the CO_2 Act[14], which the Swiss electorate narrowly rejected in

[12]Federal Act of December 23, 2011 on the Reduction of CO_2 Emissions (CO_2 Act), SR 641.71 and according to amendment AS 2024 376; BBI 2022 2651 in force as of January 1, 2025.

[13]The proposal also includes a CHF 120 levy for long travels; however, since our distances are fixed at 700 kilometers, this long-distance tax is not included in our scenario.

[14]Federal Act on the Reduction of Greenhouse Gas Emissions (CO_2 Act); BBI 2020 7847.

June 2021 (Bundesamt für Umwelt, 2021). The proposed tax is part of a broader strategy to address the environmental impact of air travel by incentivizing travelers to consider more sustainable modes of transport. In our estimation, we simulate the introduction of the CHF 30 levy by adjusting the ticket price accordingly. This scenario also serves as an example of other policies and developments that impact the relative price of air travel, such as a higher price for EU ETS allowances.

SAF quota: Here, we reflect the broader regulatory efforts in the EU and Switzerland to decarbonize the aviation sector, aligning with the net-zero emissions target established under the Paris Agreement. The EU's "Fit for 55" package, through the RefuelEU Aviation initiative, mandates increasing SAF quotas for airlines by a given year: 2% (2025), 6% (2030), 20% (2035), 34% (2040), 42% (2045), and 70% by 2050. Switzerland is adopting these SAF blending quotas, as outlined in the CO_2 Act.[15] We model the expected impact of the mandatory 6% SAF quota by 2030. The associated fuel price increase is derived from Oesingmann (2022), whose projections incorporate anticipated cost reductions over time from technological advancements. A detailed account of the calculation, resulting in an estimated increase of CHF 2.40 per ticket, is provided in Appendix G.

Expected policy 2030: The last scenario incorporates the expected effects of the mandatory 6% SAF quota by 2030, and further includes improvements in night train comfort, reflecting the recent introduction of modern night trains by Europe's leading operator, ÖBB (Austrian Federal Railways, 2024). Specifically, we model an upgrade from six-person compartments to four-person couchettes and from four-person couchettes to two-person compartments. We assume these improvements do not entail additional costs for consumers. The night train subsidy is not considered in this scenario.

6.2 Market shares

We estimate the induced changes in market shares based on the results from the Mixed NL specification (model 4 in Table 3). To determine baseline market shares, we first set

[15] Federal Act of December 23, 2011 on the Reduction of CO_2 Emissions (CO_2 Act), SR 641.71.

SAF usage to zero for all individuals (which is close enough to the current level) and assign carbon offsets only to those respondents who reported always offsetting their flight emissions.

Table 6: Market shares

	Unit	Base	(1) Pigou	(2) NT subsidy	(3) Aviation tax	(4) SAF quota	(5) EP 2030
Change induced			Price ↑ Pig. tax	NT price ↓ 20 CHF	F price ↑ 30 CHF	6% SAF F price ↑ 2.4 CHF	6% SAF F ↑ 2.4 CHF NT comfort ↑
Train chosen	%	23.7	32.8	21.4	25.8	23.8	23.4
Night train chosen	%	20.7	26.5	25.7	22.9	20.8	21.9
Car chosen	%	23.2	16.2	22.1	24.7	23.2	22.9
E-car chosen	%	0.4	0.4	0.4	0.4	0.4	0.4
Airplane chosen	%	32.1	24.2	30.4	26.1	31.8	31.4

Notes: The table shows expected changes in mode shares both for the baseline model and after changes in certain attributes. The results are based on the sample weights from Table 2.

This baseline constitutes a useful approximation of current conditions but ignores capacity constraints of night train travel and SAF. The mode shares can thus be interpreted as hypothetical demand if all modes and attributes were always available. The baseline values in Table 6 show these unconstrained mode shares for leisure trips in our representative Swiss sample. Capacity-limited and observed market shares are discussed in subsection 6.4. To estimate the effect of the scenarios we adjust the respective attribute values and predict the updated mode shares for scenarios 1 to 5. Compared to the baseline model, the Pigovian tax would lead to an increase in day train usage by 9.1 percentage points and in night train usage by 5.8 percentage points, while reducing the car and airplane shares by 7 and 7.9 percentage points, respectively. A night train subsidy would increase this share by 5 percentage points, whereas an aviation tax reduces the demand for air travel by 6 percentage points. In the 2030 scenario, the shares of train and air travel decline slightly, while the share of night trains increases.

6.3 Welfare implications

The changes in market shares form the basis for the subsequent welfare analysis. The key components of our welfare analysis include changes in consumer surplus, government revenue, and external costs. We abstract from changes in producer surplus by assuming perfect competition in the airline industry and that the regulated railway sector operates at zero profit. Due to our design that does not include a "no travel" option, all welfare changes are exclusively due to changes in travel mode, while holding travel distance and demand constant.

We calculate changes in consumer surplus by applying Equation 3 to estimate the monetized utility change at the individual level. This is the sum of the utility change associated with the behavioral adjustment and the change in monetary payments (a loss for a tax, and a gain for a subsidy). We adopt a utilitarian welfare perspective, focusing on aggregate efficiency without applying income-based or other distributional weights. Public finances include both public expenditures, such as the night train subsidy, and public revenue, such as the aviation tax. All policies are assumed to be revenue neutral, with subsidies financed through head taxes and tax revenues redistributed lump-sum. Following Jacobs (2018), we assume the marginal cost of public funds (including the marginal benefit of redistribution) to be equal to 1.

The change in external costs is calculated based on the Swiss values presented in Table 5 for the entire travel distance. We use a social cost of carbon of CHF 430 per ton of CO_2e, reflecting the recent update from Ecoplan-INFRAS (2024) for the Swiss Federal Office of Spatial Development that includes equity weighting.

The EU ETS covers CO_2 emissions from electricity production and aviation.[16] As a result, emissions from (electric) trains and airplanes are subject to the so-called "waterbed effect" (Perino, 2018); in other words, an increase in emissions by some sources within the cap will be exactly offset by a corresponding decrease in other sources, given that total emissions are equal to the (long-term) cap. While this argument is true for a fixed cap, this is not the case under the current design. At the time of writing, the cap in the EU ETS is endogenous due to rules that govern the system's Market Stability Reserve (MSR), which reduce the total cap in response to the number of unused allowances in circulation.[17]

[16]We asked respondents whether the following statement is correct: "Flights within Europe (incl. Switzerland) are subject to the EU Emissions Trading System (ETS)." Only 12% answered "yes" and 5% "no", while 83% reported not knowing the answer.

[17]Directive 2003/87/EC (OJ C, 3.6.2024, ELI: `http://data.europa.eu/eli/C/2024/3415/oj`).

To reflect this, we provide two calculations of external costs: one considering all effective emissions and another excluding climate externalities from train, night train, electric car, and air travel ("ETS considered"). We do not account for the regulation of car emissions, scheduled for implementation in 2027.[18]

Table 7: Welfare effects of the scenarios

	Unit	(1) Pigou	(2) NT subsidy	(3) Aviation tax	(4) SAF quota	(5) 2030
Change induced		Price ↑ Pig. tax	NT price ↓ 20 CHF	F price ↑ 30 CHF	6% SAF F price ↑ 2.4 CHF	6% SAF F ↑ 2.4 CHF NT comfort ↑
Consumer surplus						
Δ CS (mean)	CHF	-106.77	4.70	-9.38	-0.40	0.49
Government revenue						
Tax/Subsidy	CHF	104.24	-5.14	7.83	–	–
Net change	CHF	-2.53	-0.44	-1.55	-0.40	0.49
External cost reductions						
Climate	CHF	9.25	1.78	4.06	0.25	0.68
Climate (ETS considered)	CHF	3.97	0.62	-0.85	0.00	0.17
Environment	CHF	3.00	0.53	0.82	0.07	0.20
Local pollution & noise	CHF	-4.79	-1.08	-2.15	-0.07	-0.34
Accidents	CHF	1.38	0.21	-0.33	0.00	0.06
Congestion	CHF	0.11	0.02	-0.02	0.00	0.00
Total reduction	CHF	8.95	1.46	2.37	0.24	0.60
Reduction (ETS considered)[19]	CHF	5.40	0.30	-2.54	-0.01	0.09
Welfare change						
Δ W	CHF	6.42	1.02	0.82	-0.16	1.09
Δ W (ETS considered)[17]	CHF	5.79	-0.14	-4.09	-0.41	0.58
Δ W for Switzerland	Mio. CHF	23.73	3.77	3.03	-0.59	4.03
Δ W for Sw. (ETS considered)[17]	Mio. CHF	21.41	-0.51	-15.13	-1.50	2.14

Notes: The table shows welfare implications of each policy per person. To determine the welfare effects for the entire Swiss population, we multiply by the number of residents aged 18 to 80 (currently 6.85 million) and adjust by the share of respondents planning such a summer holiday trip (0.54).

Table 7 presents welfare implications of each policy per person, incorporating the global externalities perspective. The night train subsidy is the only policy that increases consumer surplus by design, as it enables consumers to obtain the same service at a lower cost. The 2030 scenario also raises consumer surplus, driven by the assumed free comfort upgrade from technological progress. To this consumer surplus we add the change in government

[18]Directive (EU) 2023/959 of the European Parliament and of the Council of 10 May 2023 amending Directive 2003/87/EC establishing a system for greenhouse gas emission allowance trading within the Union and Decision (EU) (OJ L 130, 16.5.2023, p. 134–202, ELI: `http://data.europa.eu/eli/dir/2023/959/oj`).

[19]Considering the EU ETS in the Pigovian scenario also affects the amount taxed per mode-kilometer with this policy. The different effect on the mode shares and the resulting external cost reductions are not displayed.

revenue (positive for taxes, negative for subsidies) that is returned or raised via lump-sum transfers, and the change in external costs. For all policies, total externalities decrease. The Pigovian tax leads to a decrease in external costs by CHF 8.95; to put this into context, the average external cost of transport is 5.88 per person per day in Switzerland (Ecoplan-INFRAS, 2024).[20] When accounting for the EU ETS, the aviation tax and the SAF quota increase external costs, as shifts away from air travel lead to additional (climate) externalities not covered by the EU ETS.

Overall, we estimate a net welfare gain for the Pigovian tax, the night train subsidy, the CHF 30 aviation tax, and the 2030 policy projection, whereas a 6% SAF quota results in a net welfare loss. However, the positive net welfare effects of the night train subsidy and the aviation tax diminish once the waterbed effect of the EU ETS is accounted for. To extrapolate the welfare effects to the entire Swiss population, we scale the per-person values by the number of residents aged 18-80 (6.85 million; Federal Statistical Office, 2023) and by 0.54, the share of survey respondents reporting plans for such a trip. This yields an affected population of 3.7 million.

Appendix H presents two supplementary welfare scenarios that incorporate night train comfort improvements, with and without an accompanying price subsidy, to capture the effects of quality improvements after infrastructure investments. These scenarios show that the observed changes in external costs are mainly driven by the night train subsidy rather than by comfort improvements.

An additional consideration is whether policymakers should incorporate only external costs incurred within Switzerland or also include global effects. Those favoring a local approach argue that it better reflects domestic impacts, while a global perspective highlights broader environmental and social implications in welfare assessments. Table 8 summarizes the welfare effects when only local externalities within Switzerland are considered, e.g., congestion, except for climate external costs. This "local view" yields similar welfare outcomes, though with different magnitudes.

[20] Based on annual external costs of CHF 15,842.6, 944, and 1,959.5 million from road, rail, and air passenger transport, respectively, and a total population of 8,738,791 (Ecoplan-INFRAS, 2024).

Table 8: Welfare effects of the scenarios: Local approach

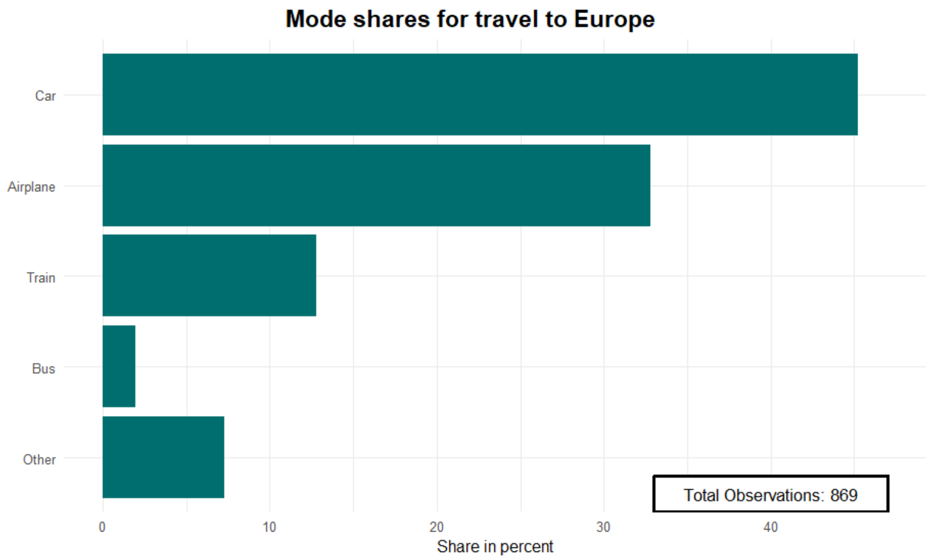
	Unit	(1) Pigou	(2) NT subsidy	(3) Aviation tax	(4) SAF quota	(5) 2030
Change induced		Price ↑ Pig. tax	NT price ↓ 20 CHF	F price ↑ 30 CHF	6% SAF F price ↑ 2.4 CHF	6% SAF F ↑ 2.4 CHF NT comfort ↑
Welfare change						
Δ W	CHF	6.63	1.25	2.02	-0.15	1.15
Δ W (ETS considered)	CHF	3.84	0.09	-2.88	-0.40	0.64
Δ W for Switzerland	Mio. CHF	24.54	4.62	7.49	-0.57	4.25
Δ W for Sw. (ETS considered)	Mio. CHF	14.20	0.34	-10.67	-1.49	2.35

Notes: This table presents the local perspective of welfare effects of each policy per person, where we assume that, on average, 2/7 of total travel distance occurs within Switzerland, reflecting the expected share of domestic travel. For climate externalities, however, all are included. To determine the welfare effects for the entire Swiss population, we multiply by the number of residents aged 18 to 80 (currently 6.85 million) and by the share of respondents planning such a trip this summer (0.54).

6.4 Adjustment to observed market shares

Figure 4 shows stated mode shares for leisure travel, based on responses from individuals planning to travel within Europe in the summer following our survey.

Figure 4: Survey question on mode shares for travel within Europe



Note: The figure illustrates the stated mode shares for summer holiday travel within Europe, based on responses from 869 individuals of our Swiss sample.

The observed distribution shows a much higher car share than in our experiment, with air and train as the next most common modes. Importantly, these mode shares are subject to capacity constraints, with (night) trains being prone to getting crowded during summer holiday season and SAF blending not yet being widely available. To account for the reported mode shares in the survey, we recalibrate the alternative-specific constants in our model. Table 9 reports the observed baseline market shares and the predicted changes for the scenarios. We split the mode share of trains (14%) in Figure 4 according to the international passenger counts reported in the business report of the Swiss Federal Railways (2024) for the entire year of 2023. Owing to the non-linearity of the underlying elasticities, the predicted changes are considerably smaller compared to Table 6. The low night train share results in a strongly negative constant, making this option unlikely to be chosen even with lower prices. Welfare effects are not reported, as capacity constraints, most notably for night trains, restrict feasible substitution patterns, which reduces the interpretability of welfare estimates.

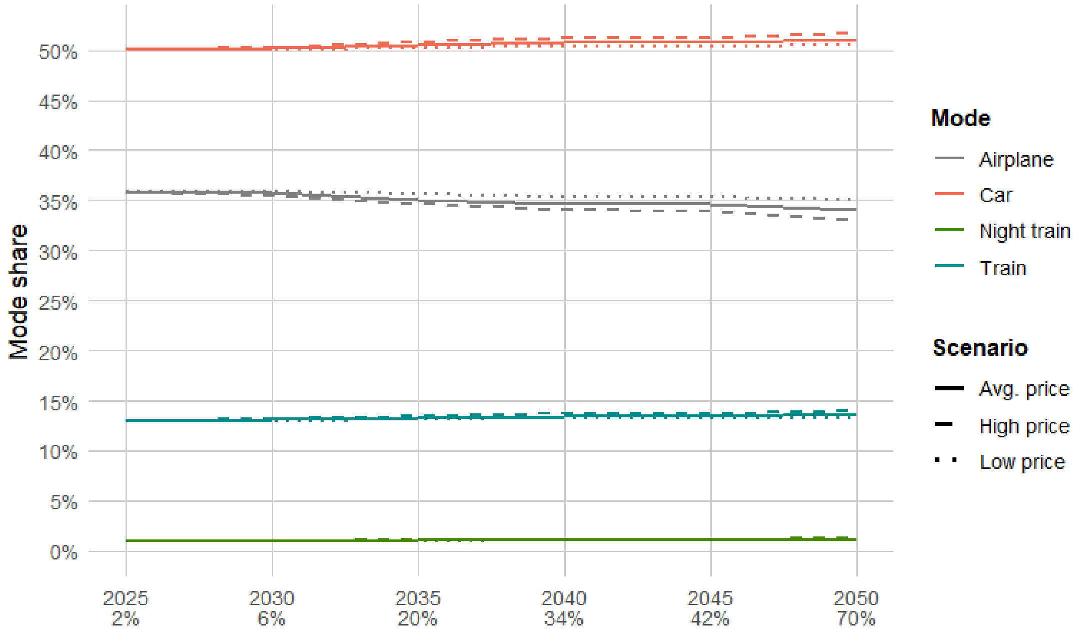
Table 9: Observed market shares

	Unit	Base	(1) Pigou	(2) NT subsidy	(3) Aviation tax	(4) SAF quota	(5) 2030
Train chosen	%	13.0	21.6	12.8	14.8	13.1	13.0
Night train chosen	%	1.0	2.2	1.7	1.4	1.0	1.3
Car chosen	%	49.1	43.2	49.0	52.1	49.3	49.2
E-car chosen	%	0.9	0.9	0.9	0.9	0.9	0.9
Airplane chosen	%	36.0	32.0	35.7	30.7	35.8	35.6

Notes: The table shows expected changes in observed mode shares both for the baseline model and after changes in certain attributes. Based on the sample weights from Table 2.

Figure 5 illustrates the expected evolution of mode shares in response to the projected increments of the SAF quota, based on the observed market shares that reflect the current situation in Switzerland. This highlights how the introduction of SAF blending affects demand starting from today's actual distribution of modes. We incorporate the anticipated decrease in SAF prices due to technological advancements over time based on Oesingmann (2022), which is explained in detail in Appendix G. As SAF quotas rise and ticket prices increase, air travel demand gradually declines, with the reduction in market share distributed across the other three modes. Even in the high-price scenario, demand shifts remain modest, but the resulting emission reductions at a 70% SAF share are substantial. The EU's recent decision to also regulate aviation's non-CO_2 effects represents a notable policy development, further strengthening emission reduction efforts and the internalization of external costs in the sector.

Figure 5: Predicted mode shares as a function of planned SAF quotas



Notes: The figure illustrates predicted mode share changes in response to already established SAF quotas (as shown in the bottom row). The dashed lines show the lower and upper bounds of expected future SAF prices, while the solid line indicates the average. The different price projections are based on Oesingmann (2022).

7 Conclusions

Addressing the challenge of reducing emissions from holiday travel requires a clear understanding of how travelers adjust their mode choices in response to policy. Focusing on leisure trips to holiday destinations that can be reached with different modes of transport, this paper evaluates such responses using a nested logit framework, providing a holistic view of demand shifts and welfare impacts. Our results depend critically on the treatment of the EU ETS: when all climate externalities are considered, welfare gains are substantial; when accounting for the waterbed effect (meaning that emissions covered by the EU ETS are held constant), the welfare effects are significantly lower. If none of the emissions reductions are absorbed via the EU ETS, all policies except the SAF quota increase overall welfare, suggesting that measures such as an aviation tax and a night train subsidy should be prioritized. In general, policy designs with values closer to the Pigovian benchmark will yield larger welfare gains. A SAF blending quota of 6% at current price levels entails a net welfare loss. However, this outcome is driven by the currently high cost, which is expected to change with technological progress.

In numerical terms, the welfare impacts amount to only a few million CHF annually across Switzerland, which reflects the narrow focus of our analysis: holiday trips in summer over rail-accessible distances. While this likely captures the main journeys for many Swiss travelers, many people take multiple holidays per year and about 14% of our sample indicated to travel outside of Europe during summer. Extending the analysis to all travel purposes throughout the year and to all regions of the world would likely yield significantly larger aggregate welfare effects.

Our study has several limitations. We cannot model the effects of capacity constraints or extensions. Our results therefore ignore that the current infrastructure does not allow all travelers who highly value the night train to choose their preferred option. However, our results indicate a high latent demand for night trains, with a mode share of 20.3%. Future capacity extensions could tap into this latent demand. Furthermore, our findings rely on stated preferences as a second-best approach, since revealed preference data is almost impossible to gather, with the non-chosen alternatives during the booking process being unknown. This introduces the potential for hypothetical bias. Carattini et al. (2025) find higher stated than revealed WTP for carbon neutrality, suggesting our estimates may represent upper bounds.

Given the representative Swiss sample and the well-developed cross-border rail network, our results are likely generalizable to other European contexts with similar infrastructure (e.g., France, Italy, and German-speaking regions). The inclusion of three language regions of Switzerland further fortifies the generalizability. However, in countries with a more developed coach market, such as France, where coaches serve a more price-sensitive segment (Crozet and Guihéry, 2018), generalizability may be somewhat reduced. This research contributes to the understanding of transport demand and provides valuable insights for policymakers in shaping sustainable transport systems. In the broader European policy landscape, where unpriced external transport costs amount to hundreds of billions annually (Van Essen et al., 2019), even moderate welfare improvements from targeted policies can meaningfully contribute to decarbonization and societal well-being.

References

Andersson, A., Engelson, L., Börjesson, M., Daly, A., and Kristoffersson, I. (2022). Long-distance mode choice model estimation using mobile phone network data. *Journal of Choice Modelling*, 42:100337.

Arbués, P., Baños, J. F., Mayor, M., and Suárez, P. (2016). Determinants of ground transport modal choice in long-distance trips in Spain. *Transportation Research Part A: Policy and Practice*, 84:131–143.

Austrian Federal Railways (2024). Annual report 2023. ÖBB-Holding AG.

Avogadro, N., Cattaneo, M., Paleari, S., and Redondi, R. (2021). Replacing short-medium haul intra-European flights with high-speed rail: Impact on CO2 emissions and regional accessibility. *Transport Policy*, 114:25–39.

Ben-Akiva, M. (1973). A disaggregate direct demand model for simultaneous choice of mode and destination. *Transportation Research Forum Proceedings 1970s*.

Berger, S., Kilchenmann, A., Lenz, O., and Schlöder, F. (2022). Willingness-to-pay for carbon dioxide offsets: Field evidence on revealed preferences in the aviation industry. *Global Environmental Change*, 73:102470.

Bernardo, V., Fageda, X., and Teixidó, J. (2024). Flight ticket taxes in Europe: Environmental and economic impact. *Transportation Research Part A: Policy and Practice*, 179:103892.

Bösehans, G., Bolderdijk, J. W., and Wan, J. (2020). Pay more, fly more? Examining the potential guilt-reducing and flight-encouraging effect of an integrated carbon offset. *Journal of Environmental Psychology*, 71:101469.

Braun, M., Grimme, W., and Oesingmann, K. (2024). Pathway to net zero: Reviewing sustainable aviation fuels, environmental impacts and pricing. *Journal of Air Transport Management*, 117:102580.

Buh, B. and Peer, S. (2024). Environmental concern and the determinants of night train use: Evidence from Vienna (Austria). *Travel Behaviour and Society*, 36:100802.

Bullerdiek, N., Neuling, U., and Kaltschmitt, M. (2021). A GHG reduction obligation for sustainable aviation fuels (SAF) in the EU and in Germany. *Journal of Air Transport Management*, 92:102020.

Bundesamt für Umwelt (2021). CO2-Abgabe und Flugticketabgabe. Technical report, Bundesamt für Umwelt. `https://www.bafu.admin.ch/bafu/de/home/themen/klima/`

dossiers/klimaschutz-und-co2-gesetz/co2-abgabe-und-flugticketabgabe.html (In German. Accessed: 28.10.2024).

Bursa, B. (2024). Mode choice and value of time on long-distance vacation trips. *Transportation Research Record*, page 03611981241252837.

Bursa, B., Mailer, M., and Axhausen, K. W. (2022). Travel behavior on vacation: transport mode choice of tourists at destinations. *Transportation Research Part A: Policy and Practice*, 166:234–261.

Carattini, S., Dvorak, F., Logar, I., and Oluk, B. (2025). Demand for Carbon-Neutral Products. Working paper.

Carroll, J., Brazil, W., Howard, M., and Denny, E. (2022). Imperfect emissions information during flight choices and the role of CO2 labelling. *Renewable and Sustainable Energy Reviews*, 165:112508.

Crozet, Y. and Guihéry, L. (2018). Deregulation of long-distance coach services in France. *Research in Transportation Economics*, 69:284–289.

Curtale, R., Larsson, J., and Nässén, J. (2023). Understanding preferences for night trains and their potential to replace flights in Europe. The case of Sweden. *Tourism Management Perspectives*, 47:101115.

de Lapparent, M., Frei, A., and Axhausen, K. W. (2009). Choice of mode for long-distance travel: Current SP-based models from three European countries. In *European Transport Conference 2009*.

Detsios, N., Theodoraki, S., Maragoudaki, L., Atsonios, K., Grammelis, P., and Orfanoudakis, N. G. (2023). Recent advances on alternative aviation fuels/pathways: A critical review. *Energies*, 16(4):1904.

Ecoplan-INFRAS (2024). Externe Effekte des Verkehrs 2021. Umwelt-, Unfall- und Gesundheitseffekte des Strassen-, Schienen-, Luft- und Schiffsverkehrs. Technical report, Bundesamt für Raumentwicklung. https://www.are.admin.ch/are/de/home/mobilitaet/grundlagen-und-daten/kosten-und-nutzen-des-verkehrs.html.

Europe on Rail (2021). European public opinion poll shows support for shifting flights to rail. Technical report, Europe on Rail. https://www.germanwatch.org/sites/default/files/2021-03-26_EU%20Rail_polling%20report_final-1.pdf (accessed: 08.10.2024).

European Commission (2021). EU transport in figures – Statistical pocketbook 2021. European Commission, Directorate-General for Mobility and Transport, doi:10.2832/27610.

Falk, M. and Hagsten, E. (2019). Short-run impact of the flight departure tax on air travel. *International Journal of Tourism Research*, 21(1):37–44.

Federal Statistical Office (2023). Altersmasszahlen der ständigen Wohnbevölkerung nach Staatsangehörigkeitskategorie und Geschlecht, 1999-2023. https://www.bfs.admin.ch/bfs/de/home/statistiken/bevoelkerung/stand-entwicklung/alter.assetdetail.32374809.html. Data source.

Fiebig, D. G., Keane, M. P., Louviere, J., and Wasi, N. (2010). The generalized multinomial logit model: accounting for scale and coefficient heterogeneity. *Marketing Science*, 29(3):393–421.

Gayda, S., Fedosseev, A., Ruyssen, M., Kouwenhoven, M., Tapia, R., and Bierlaire, M. (2024). Analysis of the stated preference survey 2021 on mode, route and departure time choices. Federal Office for Spatial Development (ARE), https://www.are.admin.ch/are/en/home/media/publications/fundamentals/analysis-of-the-stated-preference-survey-2021.html.

Gerosa, T. and Cellina, F. (2024). Who uses night trains and why? A mixed-method study profiling night train users in Switzerland. *Travel Behaviour and Society*, 37:100854.

Gössling, S., Broderick, J., Upham, P., Ceron, J.-P., Dubois, G., Peeters, P., and Strasdas, W. (2007). Voluntary carbon offsetting schemes for aviation: Efficiency, credibility and sustainable tourism. *Journal of Sustainable Tourism*, 15(3):223–248.

Hensher, D. A., Rose, J. M., and Greene, W. H. (2015). *Applied choice analysis*. Cambridge University Press.

Hess, S., Erath, A., and Axhausen, K. W. (2008). Estimated value of savings in travel time in Switzerland: Analysis of pooled data. *Transportation Research Record*, 2082(1):43–55.

Hess, S. and Palma, D. (2019). Apollo: A flexible, powerful and customisable freeware package for choice model estimation and application. *Journal of Choice Modelling*, 32:100170.

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

Jacobs, B. (2018). The marginal cost of public funds is one at the optimal tax system. *International Tax and Public Finance*, 25:883–912.

Jiang, C. and Yang, H. (2021). Carbon tax or sustainable aviation fuel quota. *Energy Economics*, 103:105570.

Kantelaar, M. H., Molin, E., Cats, O., Donners, B., and van Wee, B. (2022). Willingness to use night trains for long-distance travel. *Travel Behaviour and Society*, 29:339–349.

Keshavarzzadeh, A. H., Thut, C., Andersen, D., Lingsch, L., and Patt, A. G. (2022). Novel quota and tax regime design approach for green transition: A case study on Switzerland's aviation industry. *Energy Policy*, 171:113263.

Limtanakool, N., Dijst, M., and Schwanen, T. (2006). The influence of socioeconomic characteristics, land use and travel time considerations on mode choice for medium-and longer-distance trips. *Journal of Transport Geography*, 14(5):327–341.

McFadden, D. (1977). Modelling the choice of residential location. *Cowles Foundation Discussion Papers*, 710.

Moeckel, R., Fussell, R., and Donnelly, R. (2015). Mode choice modeling for long-distance travel. *Transportation Letters*, 7(1):35–46.

Monchambert, G. (2020). Why do (or don't) people carpool for long distance trips? A discrete choice experiment in France. *Transportation Research Part A: Policy and Practice*, 132:911–931.

Morfeldt, J., Curtale, R., Kamb, A., Larsson, J., and Nässén, J. (2023). Carbon footprint effects of shifting from flights to night trains for Swedish tourism. *Journal of Cleaner Production*, 420:138321.

Oesingmann, K. (2022). The economic impacts of EU climate policies on intra-European aviation. In *Eurasia Business and Economics Society Conference*, pages 433–452. Springer.

Pasek, J. (2018). *anesrake: ANES Raking Implementation*. R package version 0.80.

Perino, G. (2018). New EU ETS Phase 4 rules temporarily puncture waterbed. *Nature Climate Change*, 8(4):262–264.

Probst, B. S., Toetzke, M., Kontoleon, A., Díaz Anadón, L., Minx, J. C., Haya, B. K., Schneider, L., Trotter, P. A., West, T. A., Gill-Wiehl, A., et al. (2024). Systematic assessment of the achieved emission reductions of carbon crediting projects. *Nature Communications*, 15(1):9562.

Proost, S. (2024). Looking for winning policies to address the climate issue in EU-aviation. *Journal of Air Transport Management*, 115:102534.

Rich, J. and Mabit, S. L. (2012). A long-distance travel demand model for Europe. *European Journal of Transport and Infrastructure Research*, 12(1).

Rickfelder, T. and Schönberger, J. (2024). Determining the potential of international passenger rail services with applications to the European night train market. *Transportation*, pages 1–33.

Rohr, C., Fox, J., Daly, A., Patruni, B., Patil, S., and Tsang, F. (2013). Modeling long-distance travel in Great Britain. *Transportation Research Record*, 2344(1):144–151.

Sacchi, R. and Bauer, C. (2023). Mobitool v3.0. Paul Scherrer Institute, `https://www.mobitool.ch/de/tools/mobitool-faktoren-v3-0-25.html`.

Schatzmann, T. and Axhausen, K. W. (2021). Long-distance buses in Switzerland: An examination of their substitution effects for long-distance travel. Project report, ETH Zürich.

Schwirplies, C., Dütschke, E., Schleich, J., and Ziegler, A. (2019). The willingness to offset CO2 emissions from traveling: Findings from discrete choice experiments with different framings. *Ecological Economics*, 165:106384.

Small, K. A. and Rosen, H. S. (1981). Applied welfare economics with discrete choice models. *Econometrica: Journal of the Econometric Society*, pages 105–130.

Swiss Federal Office of Statistics and Swiss Federal Office of Spatial Development (2023). Mobility and Transport Microcensus 2021. `https://www.are.admin.ch/are/en/home/mobility/data/mtmc.html`. Data source.

Swiss Federal Railways (2014). Annual and sustainability report 2013. SBB Swiss Federal Railways.

Swiss Federal Railways (2024). Business report 2023. SBB Swiss Federal Railways.

Tao, X. and Zhu, L. (2020). Meta-analysis of value of time in freight transportation: A comprehensive review based on discrete choice models. *Transportation Research Part A: Policy and Practice*, 138:213–233.

Thrane, C. (2015). Examining tourists' long-distance transportation mode choices using a multinomial logit regression model. *Tourism Management Perspectives*, 15:115–121.

Train, K. E. (2002). *Discrete choice methods with simulation.* Cambridge University Press.

Turgut, E. T., Usanmaz, O., and Cavcar, M. (2019). The effect of flight distance on fuel mileage and CO2 per passenger kilometer. *International Journal of Sustainable Transportation*, 13(3):224–234.

Van Acker, V., Kessels, R., Cuervo, D. P., Lannoo, S., and Witlox, F. (2020). Preferences for long-distance coach transport: Evidence from a discrete choice experiment. *Transportation Research Part A: Policy and Practice*, 132:759–779.

Van Essen, H., Van Wijngaarden, L., Schroten, A., Sutter, D., Bieler, C., Maffii, S., Brambilla, M., Fiorello, D., Fermi, F., and Parolin, R. (2019). Handbook on the external costs of transport, version 2019. Technical report, CE Delft for the European Commission, Directorate-General for Mobility and Transport. `https://cedelft.eu/publications/handbook-on-the-external-costs-of-transport-version-2019/`.

Wardman, M., Toner, J., Fearnley, N., Flügel, S., and Killi, M. (2018). Review and meta-analysis of inter-modal cross-elasticity evidence. *Transportation Research Part A: Policy and Practice*, 118:662–681.

Yang, L., Shen, Q., and Li, Z. (2016). Comparing travel mode and trip chain choices between holidays and weekdays. *Transportation Research Part A: Policy and Practice*, 91:273–285.

Zheng, S., Wang, C., and Jiang, C. (2024). Carrot or stick? Environmental and welfare implications of sustainable aviation fuel policies. *Transportation Research Part B: Methodological*, 188:103062.

Appendices

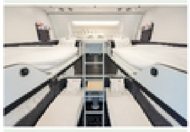
A Selected parts of the survey

Figure A.1: Explanatory text

Imagine you are planning a **one-week vacation trip** to a **European destination** of your choice. The destination is easily accessible and about **700 km** from home as the crow flies (e.g. Rome, Berlin, Barcelona or London).

We show you seven scenarios in each of which you have to decide whether you would travel by **train, night train, car or plane.**

Example scenario:

Travel cost	92 CHF	92 CHF	92 CHF	68 CHF
Travel time Door-to-door	7:40 h	6:35 h	7:40 h	4:05 h
Comfort				Economy
Sustainable fuel				☑
CO2 offsets				☒
Emissions in kg CO2e	132 kg	29 kg	44 kg	212 kg ÷ 2 = 106 kg

Some characteristics of the journey change between the scenarios, which are briefly described here. Please read the following carefully.

Travel costs (in CHF):

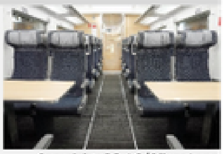
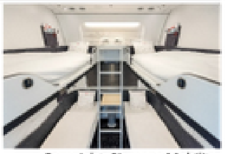
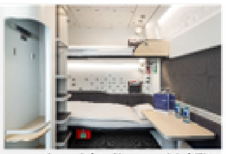
- Travel costs per person including all costs such as possible tolls for cars or CO2 offsets for air travel.

Travel time (in h:min):

- Total travel time, from door to door (incl. waiting times at the gate for flights, etc.)
- Varies depending on the scenario due to road improvements, train connections, etc.

Comfort:

- Flight always economy.
- The comfort of the car corresponds to your car.
- The following comfort levels are available for trains and night trains:

Train		Night train	
✓ 2nd class ✓ Reserved seat	 Copyright: DB AG/Oliver Lang	✓ Couchette ✓ 6-bed cabin ✓ Shared bathroom ✓ Excl. Breakfast	 Copyright: ÖBB / Marek Knopp
✓ 1st class ✓ Reserved seat	 Copyright: DB AG / Volker Emersleben	✓ Couchette ✓ 4-bed cabin ✓ Shared bathroom ✓ With locker ✓ Incl. Breakfast	 Copyright: Siemens Mobility
		✓ Sleeper cabin ✓ 2-bed cabin ✓ En-suite bathroom ✓ With locker ✓ Incl. Breakfast	 Copyright: Siemens Mobility

Sustainable fuel (Yes / No)**:**

- Only for flight option
- Sustainable fuel is a mixture of conventional kerosene and fuel obtained from renewable sources. For this, CO2 is taken from the atmosphere or recycled from plant waste and converted into synthetic fuel with the help of a chemical process. By using this blended kerosene, only half as many new greenhouse gases are emitted into the atmosphere. The saving of 50% of the emissions is shown as follows: 212 kg / 2 = 106 kg.

CO2 offsets(Yes / No):

- Only for flight option
- The CO2 emissions of the flight are offset by investments in renewable energies, energy efficiency measures and forest protection, reforestation or the renaturation of moorland.

Emissions (in kg CO2-equivalents (CO2e))**:**

- Effectively newly emitted greenhouse gas emissions of the trip, per person

All information applies to the outward journey, assuming that all characteristics remain the same for the return journey.

Figure A.2: Question for situational variable

Please think about the situation just described (a week-long trip to a European location about 700 km away). How do you imagine your trip?

- Traveling alone
- Traveling with children
- Travel with family without children (e.g. parents/relatives)
- Traveling with partner
- Traveling with friends
- Other

B Calculation of attribute levels

We carefully determine all attribute levels, including travel cost, travel time, and emissions. This section provides an overview of the data and methods used for the detailed calculations. The travel distance is fixed at approximately 700 kilometers (as the crow flies), with representative cities at this distance including Rome (684 km), London (777 km), and Berlin (671 km).[21] All calculations are based on these three destinations, with average values across the cities unless otherwise specified.

Travel time For travel time, we use values from Google Maps.[22] For instance, travel times from Zurich to Rome amount to 6:52 hours by train, 9:26 hours by car, and 1:30 hours by plane. These values serve as the basis for the orthogonalization in nGene. Since we consider door-to-door travel times, reflecting the total time relevant for consumers, we adjust the airplane option by adding 30 minutes for travel to and from the airport, along with 1.5 to 2 hours for waiting time at the gate and on the runway. For the car option, several short breaks, including potential charging stops for electric vehicles, are reflected in the total travel time. For the night train, we base the levels on the standard train travel times but also account for the deliberate slowing of night trains to allow passengers approximately 8 hours of sleep.

Travel cost Travel costs for trains and night trains are derived from fare information provided by the Swiss, Italian, German, and Austrian railway operators. The prices vary considerably depending on the railway operator and are influenced by seasonality (e.g., holidays). For air travel, we refer to prices from the popular platform Skyscanner.[23] Seasonal variations are incorporated into the cost range for flights. We also assume a fixed fee of CHF 40 for checked luggage, based on information from EasyJet.[24] For the airplane option, both airport access and egress costs, such as airport transfers, parking, or feeder transport, are implicitly included in the total travel cost, consistent with our door-to-door definition of travel time described above. The car option is distinct in that travel costs vary with the number of passengers. While our survey collects group size information, we exclude it from the cost calculations to maintain a simple survey design. Since the choice situations are presented using images, dynamically adjusting car costs based on previous answers is not feasible. This could be addressed by using percentage-based rather than absolute levels, but instead we assume that costs are shared between two passengers on average. Given an average car travel distance of 886 kilometers, an average fuel consumption of 7.48 L/100 km for Swiss cars (Sacchi and Bauer, 2023), and a fuel price of CHF 1.75/L (May 2023, in 2023 Swiss francs), this results in a base cost of CHF 57 per person and trip. Additionally,

[21] Beeline distances are estimated using https://www.luftlinie.org/.
[22] https://www.google.ch/maps
[23] https://www.skyscanner.ch/
[24] https://www.easyjet.com/

some destinations include toll charges. For instance, the toll from Como to Rome amounts to €45.90.[25] Accordingly, we vary the car travel costs between CHF 53 and 92.

Emissions Our calculation of emissions is based on Sacchi and Bauer (2023). For airplanes, we assume an aircraft with 122 seats and an average occupancy rate of 76%. Emission levels for trains depend substantially on the electricity mix of the respective country. As only parts of travel occur within Switzerland, we take the average emission intensities of the German (0.033 kg CO_2e/pkm), Italian (0.060 kg CO_2e/pkm), and French (0.013 kg CO_2e/pkm) electricity mixes, assuming 425 seats and an occupancy rate of 55%. For night trains, we apply a multiplier of 1.5 to account for the increased space per passenger. For cars, we use the average fuel consumption of the Swiss fleet from Sacchi and Bauer (2023), adjusting for an average of 2 passengers instead of 1.6 passengers as assumed in the original data. The emission levels for electric cars depend on the country's electricity mix. Assuming that the first charge occurs in Switzerland (for the outbound leg only), we calculate that a return trip requires six charges for an average electric car. One of these charges is assumed in Switzerland, with an emission intensity of 19.2 g CO_2e/pkm, while the remaining charges use the average carbon intensity of Germany, Italy, and France (36.7 g CO_2e/pkm). Sacchi and Bauer (2023) account for total emissions, not just marginal emissions related to fuel use. Therefore, we adjust the emissions associated with electricity consumption, while emissions from manufacturing, street infrastructure, maintenance, and other factors are kept at the Swiss level. Table B.1 presents the final emission intensities for each mode and the resulting overall emissions for a one-way trip.

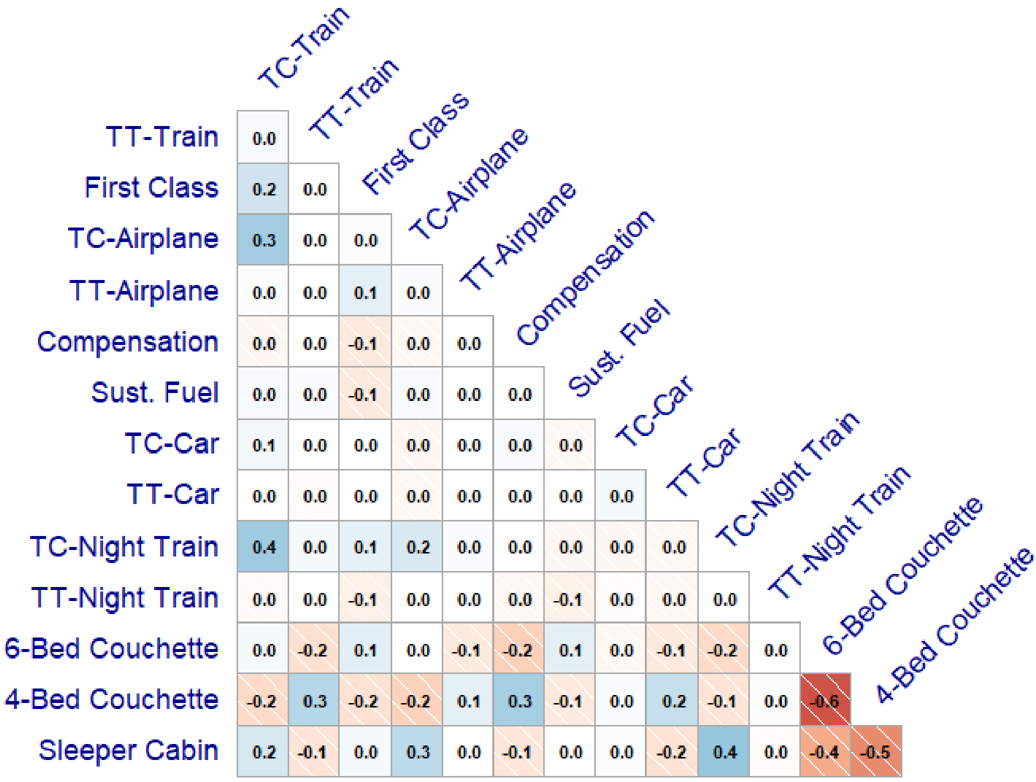
Table B.1: Emissions by mode of transport

Mode	Distance	CO_2e/pkm	Emissions
Train	920 km	0.032 kg	29 kg
Night train	920 km	0.048 kg	44 kg
Car	886 km	0.149 kg	132 kg
E-car	886 km	0.104 kg	93 kg
Airplane	718 km	0.292 kg	212 kg

[25]https://www.autostrade.it/en/pedaggio

C Correlation matrix and block design

Figure C.1: Correlation matrix of choice attributes after orthogonalizing



Notes: The figure illustrates the correlation of each attribute among the 36 choice situations presented in six blocks. The binary variables for the night train comfort levels show larger correlations as they are mutually exclusive.

Table C.1: Overview of attribute levels by block

Block	Car		Train			Night train					Airplane				
	Cost	Time	Cost	Time	1st cl.	Cost	Time	6-bed	4-bed	2-bed	Cost	Time	Offsets	SAF	Emissions
1	68	7:40	115	8:25	0	115	7:40	1	0	0	115	3:35	0	0	212
1	53	9:30	142	6:35	0	92	8.42	1	0	0	68	3:35	1	1	106
1	53	8:25	53	8:25	0	53	9:30	0	1	0	92	4:30	1	0	212
1	92	7:40	115	6:35	1	115	7:40	0	0	1	142	4:30	0	0	212
1	68	7:40	92	6:35	1	92	9:30	1	0	0	92	4:30	0	1	106
1	92	9:30	53	7:40	0	92	7:40	0	1	0	115	3:35	1	1	106
2	68	8:25	142	7:40	0	115	8:25	0	0	1	142	4:30	0	1	106
2	92	8:25	115	8:25	0	92	9:30	0	1	0	68	3:35	0	0	212
2	92	8:25	92	7:40	1	53	7:40	0	1	0	115	3:35	1	0	212
2	53	8:25	92	8:25	1	142	9:30	0	1	0	92	4:30	0	0	212
2	53	9.50	142	8:25	1	142	8:25	0	1	0	92	4:30	1	0	212
2	92	7:40	92	6:35	0	92	7:40	0	1	0	68	4:30	1	0	212
3	68	9:30	53	7:40	0	115	7:40	0	1	0	115	4:30	1	1	106
3	53	8:25	92	6.58	0	53	7:40	0	1	0	68	3:35	1	1	106
3	68	8:25	142	8:25	1	115	8:25	1	0	0	115	3:35	0	1	106
3	92	9:30	92	7:40	0	142	9:30	0	0	1	115	3:35	1	0	212
3	53	7:40	142	6:35	0	142	9:30	0	0	1	142	3:35	1	0	212
3	68	9:30	53	6:35	0	92	9:30	1	0	0	92	4:30	0	1	106
4	92	8:25	142	8:25	0	142	9:30	0	1	0	142	3:35	1	1	106
4	53	8:25	142	8:25	0	92	7:40	0	1	0	142	4:30	1	1	106
4	53	8:25	53	8:25	0	92	8:25	0	0	1	92	3:35	0	1	106
4	68	7:40	53	6:35	0	53	9:30	1	0	0	115	3:35	0	0	212
4	92	7:40	115	8:25	1	53	9:30	1	0	0	115	4:30	1	1	106
4	92	9.50	92	7:40	1	53	7:40	1	0	0	68	3:35	0	1	106
5	68	9:30	92	7:40	0	92	8:25	0	1	0	142	4:30	0	1	106
5	53	8:25	53	8:25	0	53	8:25	0	1	0	68	4:30	0	0	212
5	68	7:40	53	6:35	0	115	9:30	0	1	0	68	3:35	1	1	106
5	68	9:30	115	7:40	1	142	8:25	0	1	0	68	3:35	0	0	212
5	68	7:40	115	7:40	1	142	8:25	0	0	1	92	4:30	1	1	106
5	92	9:30	142	6:35	0	115	8:25	1	0	0	115	4:30	0	0	212
6	68	7:40	53	8:25	0	115	7:40	1	0	0	92	3:35	1	0	212
6	53	9:30	115	6:35	1	92	8:25	0	0	1	142	3:35	0	0	212
6	92	7:40	115	7:40	0	142	7:40	0	0	1	68	4:30	0	1	106
6	53	7:40	142	7:40	0	92	8:25	1	0	0	142	3:35	0	1	106
6	53	8.42	92	6:35	1	115	7:40	1	0	0	115	4:30	1	0	212
6	92	9:30	115	7:40	0	53	9:30	0	1	0	92	4:30	1	0	212

D Distribution of respondents across travel scenarios

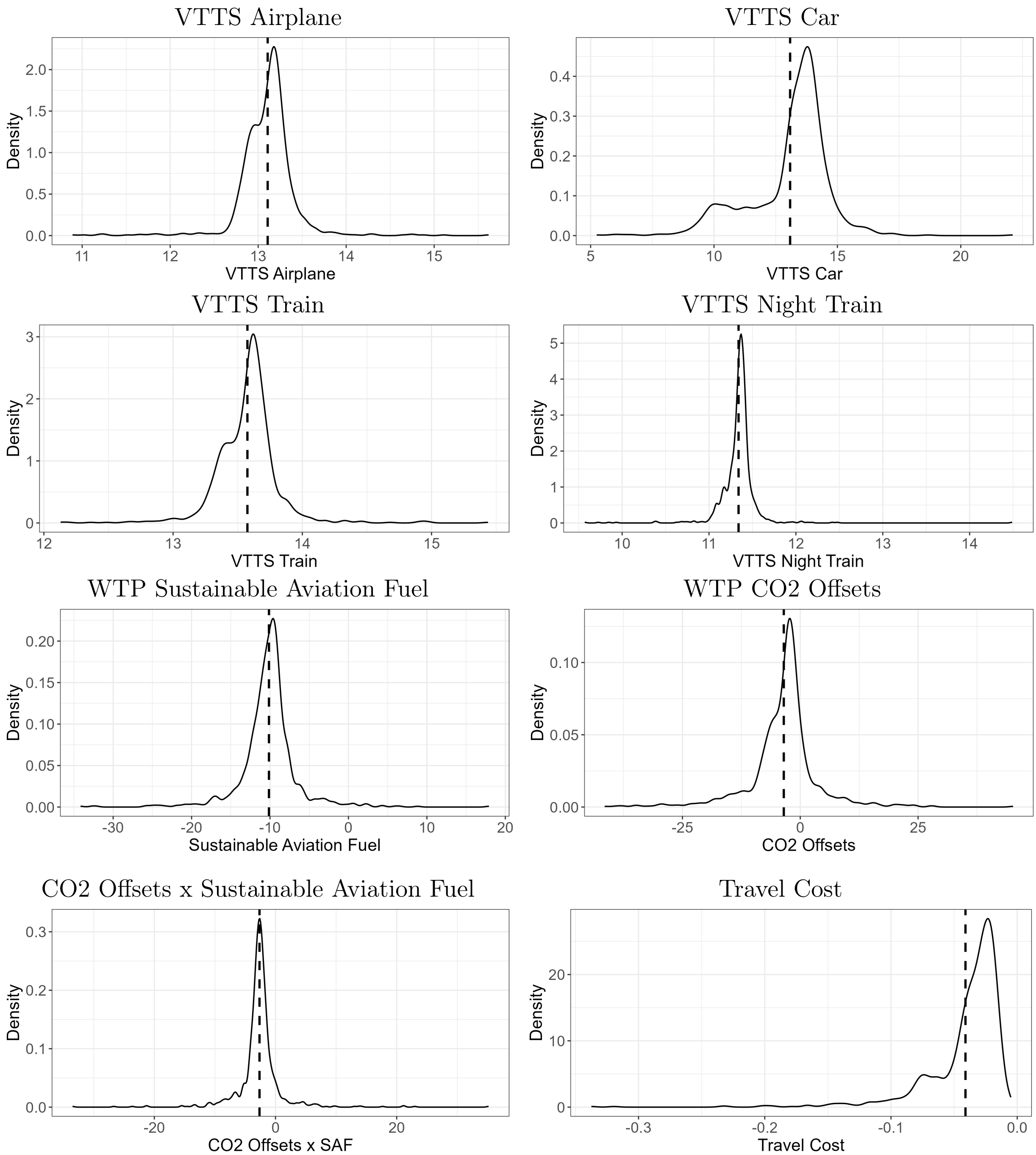
Table D.1: Distribution of respondents and total observations across travel scenarios

Category	Level	Alone	With children	With family	With partner	With friends	Other
Access to	Yes	67.5	93.9	89.1	88.8	80.0	100.0
car	No	32.5	6.1	10.9	11.2	20.0	0.0
Access to	Yes	3.5	7.0	1.1	4.0	1.8	0.0
e-car	No	96.5	93.0	98.9	96.0	98.2	100.0
Age	Below 36 years	24.6	12.6	29.3	24.7	46.7	0.0
	Between 36 and 60	56.1	84.1	50.0	43.0	34.5	42.9
	Above 60 years	19.3	3.3	20.7	32.2	18.8	57.1
Gender	Female	40.4	47.7	50.0	50.5	60.0	57.1
	Male	59.6	52.3	50.0	49.5	40.0	42.9
Education	Mandatory	7.0	2.8	8.7	1.5	4.8	0.0
	Secondary	37.7	33.2	53.3	44.7	50.3	42.9
	Tertiary	55.3	64.0	38.0	53.8	44.8	57.1
Monthly	Below 10,000 CHF	80.7	51.4	72.8	54.3	70.3	85.7
household	Above 10,000 CHF	11.4	42.1	20.7	34.1	16.4	0.0
income	Unknown	7.9	6.5	6.5	11.6	13.3	14.3
Language	German	67.5	57.9	44.6	65.5	62.4	42.9
	French	17.5	23.8	29.3	19.8	21.2	28.6
	Italian	14.9	18.2	26.1	14.8	16.4	28.6
Urbanity	Urban	71.9	56.5	59.8	60.9	66.1	85.7
level	Agglomeration	14.9	29.0	20.7	22.9	21.8	14.3
	Rural	13.2	14.5	19.6	16.2	12.1	0.0
Individuals		114	214	92	481	165	7
Observations		684	1,284	552	2,886	990	42

Notes: The table reports the distribution of respondents across the six travel scenarios defined by the situational variable. For each scenario, it shows the share of socio-demographic groups (in percent). The two bottom rows indicate the total number of individuals and the corresponding number of choice observations per scenario.

E Posterior distributions

Figure E.1: Posterior distributions of model 4 in Table 3



Notes: The figures show the distribution of conditional parameter means from model 4 in Table 3, used for the welfare calculations. The dashed line marks the average across 1,073 means.

F Robustness of regression results

Table F.1 presents robustness checks using (non-nested) MNL and mixed MNL models, including one with a common error component (EC) for the two train alternatives. Model 3 imposes log-normal distributions to enforce expected signs for the coefficients of SAF and carbon offsets, as well as the interaction between them. However, this specification does not improve model fit and produces substantial dispersion in some coefficients.

Model 4 shows a specification that accounts for respondents' relative income bracket in the cost coefficient (see Federal Office for Spatial Development, 2024). Formally, the log-normal cost coefficient is redefined as

$$\beta_{cost,n} = -\exp(b + \sigma d_N) \cdot \left[\left(\frac{\text{income}_n}{\text{avg. income}} \right)^{\lambda_{\text{inc}}} r_n + (1 + \alpha_{\text{noIncome}})(1 - r_n) \right],$$

where $d_N \sim N(0,1)$ and λ_{inc} denotes the income elasticity of cost sensitivity. The coefficient α_{noIncome} together with the dummy $r_n \in \{0,1\}$ separates respondents without income information ($r_n = 0$) from the estimation of the elasticity. Household income is reported in nine brackets of CHF 2,000 each and transformed into a continuous variable using the bracket medians; for the bottom and top categories, CHF 1,500 and CHF 18,000 are assumed, respectively. We do not include this specification in the main results, as the income elasticity yields only negligible improvements in model fit and λ_{inc} is statistically insignificant ($p > 0.05$).

The table is complemented by an EC logit model, following Train (2002). We add a normally distributed error component, $\eta_n \sim \mathcal{N}(0, \sigma_{\text{EC}})$, to the utility functions of both train alternatives. This common factor induces correlation in their unobserved utilities, analogous to a nested logit. We ultimately prefer the NL model, as the error component coefficient is not significantly different from 1 and model fit is identical to the comparable NL specification.

Table F.1: Robustness regression estimates

	Coefficient	(1) MNL	(2) MMNL ~ $\mathcal{N}$	(3) NL ~ *Log*	(4) NL Income	(5) ECL
Travel Cost	Travel Cost	-0.011***	-3.585***	-3.842***	-3.79***	-3.609***
		(0.001)	(0.069)	(0.089)	(0.091)	(0.095)
	$\sigma_{\text{Travel Cost}}$		-0.942***	-1.035***	-0.971***	-0.886***
			(0.055)	(0.06)	(0.095)	(0.141)
	λ_{inc}				0.236	
					(0.217)	
	α_{noIncome}				0.241	
					(0.318)	
Travel Time	TT-Train	26.544***	14.95***	14.689***	16.944***	15.641***
		(3.525)	(1.189)	(1.201)	(2.06)	(1.354)
	$\sigma_{\text{TT-Train}}$		-0.437***	-1.001***	-2.021***	-0.288***
			(0.226)	(0.15)	(0.355)	(0.298)
	TT-Night Train	13.606***	12.438***	12.116***	13.564***	12.658***
		(3.112)	(1.056)	(1.454)	(1.871)	(1.258)
	$\sigma_{\text{TT-Night Train}}$		-2.862***	-1.435***	-2.519**	-1.536*
			(0.279)	(0.452)	(1.152)	(0.991)
	TT-Car	13.257***	15.291***	14.528***	17.22***	14.78***
		(3.278)	(1.096)	(1.135)	(2.979)	(1.095)
	$\sigma_{\text{TT-Car}}$		-0.348***	-2.852***	-1.347*	1.943
			(0.28)	(0.411)	(0.968)	(0.843)
	TT-Airplane	12.821**	16.777***	16.538***	15.615***	19.277***
		(4.69)	(2.07)	(2.35)	(3.123)	(3.049)
	$\sigma_{\text{TT-Airplane}}$		12.661***	7.085***	0.467	7.102***
			(0.862)	(0.814)	(3.297)	(1.358)
Comfort	First Class	-5.559	-3.717	-5.135	-4.78	-2.546
		(4.635)	(2.819)	(3.755)	(4.723)	(3.622)
	$\sigma_{\text{First Class}}$		-25.866***	-24.111***	-27.051***	-26.205***
			(4.714)	(3.577)	(3.525)	(6.01)
	Couchette (4-Bed)	-11.914.	-5.379	-1.764	-3.292	-4.891
		(7.24)	(3.859)	(3.78)	(4.804)	(4.875)
	$\sigma_{\text{Couchette (4-Bed)}}$		-19.931***	-19.185**	-9.445	-7.269
			(3.94)	(6.431)	(12.171)	(7.728)
	Sleeper Cabin	-16.409*	-6.96.	-6.944	-8.023	-8.981.
		(6.806)	(3.762)	(5.354)	(6.73)	(4.782)
	$\sigma_{\text{Sleeper Cabin}}$		-43.439***	-40.662***	-37.658**	-42.208***
			(5.459)	(9.493)	(12.004)	(6.696)
Emissions	Carb. Offsets	-9.135	-4.953	-0.647	-5.402	-5.887
		(7.285)	(4.062)	(4.206)	(5.808)	(4.469)
	$\sigma_{\text{Carb. Offsets}}$		13.768***	1.506	24.688***	9.421
			(1.99)	(1.633)	(6.759)	(7.358)
	SAF	-14.489*	-9.959*	-5.548***	-10.259.	-9.913*
		(6.541)	(4.358)	(0.552)	(5.575)	(4.401)
	σ_{SAF}		9.905*	0.085.	10.79*	9.555*
			(3.847)	(0.483)	(4.841)	(4.064)
	Carb. Offsets x SAF	4.578	-0.955	1.532	-1.566	-0.492
		(11.088)	(6.176)	(1.267)	(6.557)	(6.086)
	$\sigma_{\text{Carb. Offsets x SAF}}$		24.742***	-1.551***	9.652.	32.338***
			(3.544)	(0.7)	(4.774)	(4.426)
Model fit	LL(final)	-8312	-5210.1	-5208.5	-5198.3	-5205.7
	McFadden R^2	0.024	0.386	0.386	0.387	0.387
	AIC	16651.9	10478.2	10477	10460.5	10471.4
	BIC	16746.7	10674.5	10680.1	10677.2	10674.5
	Avg. Likelihood	0.281	0.485	0.485	0.486	0.485

Notes: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $.\,p < 0.1$. Models 1-2 report MNL and Mixed MNL estimates without nesting. *Continued.*

	Coefficient	(1) MNL	(2) MMNL ~ $\mathcal{N}$	(3) NL ~ *Log*	(4) NL Income	(5) ECL
Constants	ASC Train	1.327***	1.673***	1.555***	2.427***	1.359**
		(0.332)	(0.321)	(0.266)	(0.665)	(0.518)
	$\sigma_{\text{ASC Train}}$		-1.972***	-1.095***	-0.986***	-1.995***
			(0.348)	(0.464)	(0.353)	(0.224)
	ASC Night Train	0.127	0.679*	0.83**	1.575*	0.375
		(0.331)	(0.321)	(0.293)	(0.671)	(0.479)
	$\sigma_{\text{ASC Night Train}}$		-2.496***	-1.899***	-1.856***	-2.504***
			(0.3)	(0.359)	(0.416)	(0.222)
	ASC Car	0.123	0.087	-0.551	0.592	-0.408
		(0.355)	(0.413)	(0.455)	(1.28)	(0.474)
	$\sigma_{\text{ASC Car}}$		-5.64***	-5.612***	-5.521***	-5.491***
			(0.373)	(0.372)	(0.559)	(0.416)
	$\sigma_{\text{ASC Airplane}}$		-4.597***	-4.713***	-4.903***	-4.74***
			(0.278)	(0.288)	(0.28)	(0.288)
Error-Component	σ_{EC}					1.445.
						(0.268)
Nesting	λ			0.575***	0.567***	
				(0.077)	(0.077)	
Model fit	LL(final)	-8312	-5210.1	-5208.5	-5198.3	-5205.7
	McFadden R^2	0.024	0.386	0.386	0.387	0.387
	AIC	16651.9	10478.2	10477	10460.5	10471.4
	BIC	16746.7	10674.5	10680.1	10677.2	10674.5
	Avg. Likelihood	0.281	0.485	0.485	0.486	0.485

Continuation: Models 3-4 are nested with (3) using log-distributions to enforce the interaction between Carb. Offsets and SAF to be negative. Model 4 incorporates income elasticity in the cost parameter. A dummy variable for "no income" is included for respondents who did not report their income. Model 5 adds a common error component (ECL) for the two train alternatives. The reference category is airplane. Mixed models are estimated using 1,000 MLHS draws. Robust standard errors in parentheses.

G Calculation of SAF prices

Although SAF quotas have become a central element of the EU's aviation decarbonization strategy, global production capacity remains limited. The combination of low output volumes and the early-stage development of different SAF technologies results in considerable variation in reported fuel prices (Braun et al., 2024). As demand increases under the EU quotas and technological progress continues, production costs are expected to decline, leading to more stable prices in global markets (Bullerdiek et al., 2021). We do not distinguish between specific SAF technologies but apply a general price to capture the overall effect on reducing emissions. The prices are based on the projections in Oesingmann (2022), and reprinted in the "Price 1" and "Price 2" columns of Table G.1. The author assumes a price reduction of 0.5% and 1.5% for the two scenarios, respectively. While Oesingmann (2022) also includes a third and higher price path, recent market developments and updated findings in Braun et al. (2024) and Detsios et al. (2023) suggest that only the two lower price paths are applicable. The "Avg. price" column represents the average of these two price scenarios and serves as our baseline projection.

To calculate the premium on the airfare for different SAF shares, fuel consumption data for short- to medium-haul flights were sourced from Turgut et al. (2019), indicating a consumption rate of 7.5 kg per nautical mile. Converting to liters per kilometer and dividing by the average number of revenue passengers (92, according to Sacchi and Bauer (2023)) results in an average fuel consumption of 37.4 liters of kerosene per passenger for a 700 km flight. The premium is then calculated by

$$\text{Premium} = 37.4219 \text{ L} * \text{Quota} * (\text{Price}_{\text{SAF}} - 0.58)$$

where CHF_{2023} 0.58/L represents the 2010–2021 average price of conventional aviation fuel (Braun et al., 2024). The last column in Table G.1 presents the ticket premium for a 50% SAF blending ratio in each projected year, based on the average price. This illustrates our SAF share of 50% and its associated costs (Figure 1).

Table G.1: SAF price calculations

Year	Quota	Price 1	Price 2	Avg. price	Premium 1	Premium 2	Avg. premium	50% quota premium
2025	2%	1.21	2.16	1.69	0.49	1.20	0.84	21.07
2030	6%	1.18	2.00	1.59	1.40	3.24	2.32	19.34
2035	20%	1.15	1.86	1.51	4.43	9.73	7.08	17.70
2040	34%	1.13	1.73	1.43	7.26	14.85	11.06	16.26
2045	42%	1.10	1.59	1.35	8.49	16.24	12.36	14.72
2050	70%	1.07	1.48	1.27	13.34	24.11	18.72	13.37

Notes: Prices (from Oesingmann (2022)) and flight ticket premiums in CHF_{2023}/L by year and SAF quota. The rightmost column reports the premium for a 50% SAF blend.

H Welfare effects of alternative scenarios

The two additional scenarios shown in Table H.1 disentangle the effects of service-quality improvements from those of the night train subsidy. A comfort upgrade alone yields a higher welfare gain than a stand-alone subsidy, as quality improvements raise consumer surplus and, under the zero-profit assumption, generate no additional costs. The subsidy, in contrast, produces larger reductions in external costs but is fiscally more expensive. The combined scenario reflects both channels and allows us to separate the welfare contributions of quality versus price incentives.

Table H.1: Welfare effects of alternative scenarios

	Unit	(1) NT comfort upgrade	(2) NT subsidy & comfort upgrade
Change induced		NT comfort ↑	NT price ↓ 20 CHF NT comfort ↑
Consumer surplus			
Δ CS (mean)	CHF	0.88	5.78
Government revenue			
Tax/Subsidy	CHF	–	-5.36
Net change	CHF	0.88	0.42
External cost reductions			
Climate	CHF	0.51	2.20
Climate (ETS considered)	CHF	0.17	0.79
Environment	CHF	0.15	0.65
Health	CHF	-0.32	-1.40
Accidents	CHF	0.06	0.27
Congestion	CHF	0.00	0.02
Total reduction	CHF	0.41	1.74
Reduction (ETS considered)	CHF	0.07	0.33
Welfare change			
Δ W	CHF	1.29	2.16
Δ W (ETS considered)[17]	CHF	0.95	0.75
Δ W for Switzerland	Mio. CHF	4.77	8.00
Δ W for Sw. (ETS considered)[17]	Mio. CHF	3.50	2.78

Notes: The table shows welfare implications of each policy per person. To determine the welfare effects for the entire Swiss population, we multiply by the number of residents aged 18 to 80 (currently 6.85 million) and adjust by the share of respondents planning such a summer holiday trip (0.54).